Auditors are Known by the Companies They Keep*

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Abstract

We study the role of reputation in auditor-client matching. Using 1.2 million employment records from US broker-dealers, we find that broker-dealer clients of the same auditor have similar financial adviser misconduct profiles. Our estimates indicate that variation in client misconduct behavior is nearly half as important as variation in client size in explaining matches. Auditors adjust their portfolios when presented with new information about client behavior, and those with the most significant reputation concerns are least likely to deal with high misconduct clients. Finally, we find that an auditor's reputation for accepting high misconduct clients predicts their new clients' future misconduct. Together, our results present new evidence on how reputation affects audit relationships, and the consequences of auditors' reputation concerns for client behavior. Our results also indicate an unintended consequence of audit mandates: non-discerning auditors emerge to serve clients with low endogenous demand for auditing.

JEL Classification: M21, M41, M42, G24, G28, D14, D18

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1. Introduction

The role of reputation risk in the audit market has a long history in the accounting literature. Reputation is considered important in this market because of the information asymmetry that exists between clients and auditors. Auditing is a ‘credence good’ in which customers cannot fully understand the quality of the service they purchase (e.g., Causholli and Knechel, 2012). As such, clients often rely on information about the auditor’s reputation to assess quality. This reputation information can include signals deriving from the behavior of the auditor’s other clients—for example, violations of professional standards governing fiduciary duties and conflicts of interest, as well as incidents of fraud or regulatory sanctions.

Clients relying on auditor reputation creates three implications for auditor behavior. First, high-reputation auditors have incentives to deliver a sufficient level of audit quality to avoid fraud or misreporting incidents that harm their reputation and jeopardize their future rents (DeAngelo, 1981; Weber, Willenborg and Zhang, 2008; Skinner and Srinivasan, 2012). That is, auditors will exert effort to prevent their clients from making reporting decisions that could hurt the auditor’s reputation (Lennox and Li, 2014; Coffee, 2019). Second, auditors will charge a risk premium to account for the reputation risk that a given client presents (Morgan and Stocken, 1998; Johnstone and Bedard, 2001; Johnstone and Bedard, 2004a; Lyon and Maher, 2005). A third, less explored implication is that auditors protect their reputations through portfolio management—actively screening the clients they accept and keep (Johnstone and Bedard, 2004b). A market characterized by sellers and buyers screening one another is referred to as having two-sided matching (Roth and Sotomayor, 1992; Azevedo and Leshno, 2016). In such a market, the benefit a customer receives from a seller is contingent, in part, on the characteristics of the seller’s other customers.

Efforts to study how reputation concerns influence auditors’ client acceptance and continuance decisions face a common challenge that has stymied other audit research on reputation risk:

separating issues relating to reputation versus litigation.[1] Additionally, audit research predominantly studies what are widely considered to be the most reputable auditors (Big 4 accounting firms) and the most reputable clients (large, publicly-traded companies). Analyses of matches between only the most reputable auditors and clients may lack the necessary variation to fully assess the importance of reputation to auditing. Similarly, by design, prior research that investigates how an auditor prices the business risk of existing clients cannot evaluate more fundamental questions about which clients an auditor accepts and avoids altogether. Matching frameworks, such as those used to understand marriages (Becker, 1973), student-school matches (Abdulkadiroğlu, Pathak, and Roth, 2005, 2009), and mergers (Focarelli, Panetta, and Salleo, 2002; Akkus, Cookson, and Hortacsu, 2015), are better suited to these sorts of investigations.

In this paper, we investigate three predictions of two-sided matching based on reputation in audit markets. First, an auditor's clients "look alike" in terms of their track record of misconduct behavior. Second, an auditor's willingness to accept and continue with certain clients depends on both the auditor's reputation and the transparency of client misconduct information. Third, it is possible to predict a client's future behavior by the behavior of the auditor's other clients.

We investigate these predictions in the US broker-dealer (BD) market. BDs provide financial planning services and execute over $40 trillion of transactions annually on behalf of investors or themselves. The BD setting offers two useful features for investigating the role of reputation in auditor-client matching. First, individual advisers must register with the Financial Industry Regulatory Authority (FINRA), and their employment history and misconduct incidents (if any) are public. For each incident, we observe the date, adviser and employer identity, as well as a description of the misconduct and outcomes including sanctions, terminations, and industry bans. We use

[1] For example, when discussing the potential for reputation risk to affect audit quality, DeFond and Zhang (2014) argue that "the US evidence (on reputation risk) is limited and much of the evidence is inextricably confounded by high litigation risk" (p. 297).

the misconduct records for over 1.2 million financial advisers to develop a proxy for BD client behavior that is potentially relevant to auditor reputation.[2] Crucial to our purposes of studying reputation separate from litigation risk, the misconduct incidents do not involve financial reporting (rather, e.g., they may involve complaints about unsuitable investments or excessive trading). Indeed, an exhaustive search for BD auditor litigation in the US yields only nine cases over the past 50 years. Furthermore, only two cases involve the type of customer-facing misconduct we study, and both were frauds perpetrated by owner-officers rather than advisers.

Second, all BDs must undergo audits and file financial statements with the SEC, so we observe the complete client portfolio for all audit firms in this market, as opposed to observing only the public clients of the largest auditors. Each year, 4,000 US BDs contract with 700 audit offices of 400 auditors, ranging in size and BD client exposure. BDs have anywhere from one to tens of thousands of financial adviser employees. At the typical BD, 12% of advisers have a misconduct incident on their record; however, some BDs have a zero tolerance policy, while at others adviser misconduct is common (Egan, Matvos, and Seru, 2019). Thus, the BD setting is well suited to studying auditor reputation: we observe client misconduct incidents that can harm the auditor's reputation but pose scant litigation risk, we observe all auditor-client matches, and there exists rich heterogeneity in BD characteristics that enables us to isolate the role of reputation in matching.

We begin our analyses by studying new relationships (i.e., matches) between BD clients and individual audit offices. We compare the misconduct records of the new BD clients and their auditor's existing clients, where misconduct is measured the year before the match to avoid a spurious relation. After controlling for BD size, business model, location, ownership, internal control weaknesses, and time effects, we find an economically and statistically significant relation between new and existing client misconduct. Specifically, client misconduct records are nearly half

[2] In this respect our approach is similar to Davidson, Dey, and Smith (2015) and Pacelli (2018), who develop proxies for managerial style and corporate culture, respectively.

as important as client size in explaining auditor-client matching—notable because size matching is mechanical (small auditors do not have the ability to accept large clients). These findings are not sensitive to the specification we use (non-parametric analysis, linear regression, multinomial logit matching regression, or structural estimation) or the manner in which we control for BD size and business model. Additionally, misconduct matching emerges in clients of all sizes, business models, and ownership types, thereby reducing generalizability concerns about our findings (e.g., Glaeser and Guay, 2017).

Of course, misconduct incidents can inform the auditor about management quality and the likelihood of reporting fraud. Then, one might wonder if the matching we find simply reflects a form of opinion shopping (Lennox, 2000; Newton et al., 2016; Chen et al., 2016), which would favor a litigation risk interpretation. However, the significance and magnitude of our results is the same if we eliminate the misconduct incidents most pertinent to audit risk (e.g., fraud, forgery, misappropriation) as well as the clients where audit risk is inherently higher (those BDs that are publicly held, maintain custody of investor assets, and have internal control weaknesses). The evidence thus suggests that auditors' heterogeneous concerns about reputation, and not just litigation risk, are important to explaining auditor-client relationships.[3]

We then investigate three ways in which auditor selectivity over their client portfolio relates to misconduct matching. First, we examine the relation between an auditor's non-BD portfolio and the misconduct profile of their BD clients. Bank and IPO clients are particularly sensitive to auditor reputation, given information asymmetry problems and litigation risk (Willenborg, 1999; Pittman and Fortin, 2004; Li, McNichols, and Raghunandan, 2018). We therefore expect

[3] The fallout from the recent discovery of widespread sales misconduct at Wells Fargo helps illustrate this result. Wells Fargo employees opened millions of fake customer accounts, leading several lawmakers to publicly question the quality of their auditor's (KPMG) work and call for a PCAOB investigation. While KPMG asserts that "not every illegal act has a meaningful impact on a company's financial statements", KPMG's awareness of sales misconduct could harm its reputation (McKenna and Riquier, 2017).

auditors with bank or IPO clients to be disinclined to accept or keep high misconduct BDs. We find less misconduct among BD clients of auditors with banks or IPO firms. Our IPO finding applies even across offices within the same audit firm, indicating that both office- and firm-level variation in reputation concerns are relevant to portfolio management decisions.

Second, we study continuance decisions. While we find that auditor-client pairs that are mismatched with respect to misconduct separate sooner than other pairs, the shortest of all relationships we observe are those involving auditors with high reputation and clients with high misconduct. That is, high misconduct BDs separate significantly sooner from auditors dealing primarily with low misconduct clients than from auditors dealing with other high misconduct clients. This evidence complements audit firm portfolio management research relating auditor resignations to litigation risk (Krishnan and Krishnan, 1997; Shu, 2000; Kim and Park, 2014).

Third, we shed light on the role of information asymmetry in auditor-client matching by studying the 2007 modernization of the BrokerCheck website. Prior to 2007, the website primarily contained BD-level registration information. A user could make a phone or written request for a summary report about any individual adviser, and FINRA would respond to requests via mail or email. If a summary report revealed misconduct, the user would then need to file a subsequent request for details of the incident (NASD, 2007). The modernized website provides free, instantaneous, searchable information about all advisers and their misconduct, thus greatly reducing the cost of identifying BD misconduct, but providing no new information to BDs about auditors. We show that post-modernization, auditors increasingly concentrate their client portfolios in a given misconduct segment, suggesting that transparency of BD behavior intensifies misconduct matching. These results also reinforce that auditors' heterogeneous preferences with respect to client reputation are important to understanding audit relationships.

We conclude our analyses by highlighting an important implication of reputation-based matching: the identity of a BD's new auditor predicts the BD's future misconduct over-and-above the BDs' own misconduct record. We model future misconduct as a function of the BD's current and past misconduct, their new auditor's reputation (based on the misconduct of their existing clients), as well as a host of business model and time controls. We find that those BDs matching with the least reputable auditors subsequently engage in significantly more misconduct than otherwise similar BDs matching with other auditors. Our analysis is not intended to discern between treatment and selection explanations for this predictive relation. Nevertheless, our findings suggest that in markets where auditor reputation is important, the identity of a client's auditor can be informative about the client's future behavior.

We offer several contributions. First, research on reputation in audit markets has been hampered by difficulties separating reputation from litigation risk (DeFond and Zhang, 2014). Two exceptions are Weber et al. (2008) and Skinner and Srinivasan (2012), who study low litigation risk settings and show how the financial statement fraud of one client affects other clients of the same auditor.[4] We advance this research by showing that non-reporting misconduct is important to auditor acceptance and continuance decisions, even in cases where the client's audit risk is inherently low. Under the plausible assumption that non-reporting misconduct has little effect on an auditor's litigation risk but does affect reputation risk, our findings highlight the important role of reputation in understanding audit market structure. Thus, combined with prior work focused on how auditors price business risk, our evidence portrays a broader picture of how reputation concerns affect auditor-client relationships.

Second, our setting allows us to study the entire set of auditors and clients in a market, which enables us to document meaningful variation in client acceptance and continuance deci-

[4] See also Donelson, Ege, and Leiby (2019) who find that non-accounting securities fraud lawsuits against one client reduce the fees that other clients pay the same auditor.

sions, and link this variation to auditors' heterogeneous reputation concerns. Given that some auditors appear quite selective in their client choices, our results suggest caution to research inferring causal treatment effects from auditing or assuming that an auditor-client match is primarily the choice of the client.[5]

Third, our findings are relevant to recent models studying how the matching process depends on the information environment (Hao, 2008; Liu et al., 2014). Empirical matching research typically presumes full information. But in most settings including audit markets, parties are asymmetrically informed, particularly about transgressions such as misconduct. While theory has offered competing predictions about the effects of more information on matching, we find greater portfolio concentration following an increase in transparency.

Last, our findings add to the growing work concerned with BD misconduct (Dimmock and Gerken, 2012; Egan et al., 2017, 2019; Dimmock, Gerken, and Graham, 2018; Honigsberg and Jacob, 2018; Parsons, Sulaumen, and Titman, 2018; Charoenwong, Kwan, and Umar, 2019; Law and Mills, 2019). Recent work shows that financial misconduct not only involves direct losses to investors, but also has real effects on investor participation in the stock market (Gurun, Stoffman, and Yonker, 2017). We find that auditor reputation is predictive of future BD misconduct. Therefore, our results are relevant to academics, investors, and regulators seeking to understand BD misconduct. Our results are also relevant to discussions of audit mandates, which are often aimed at protecting investors. Our evidence suggests a potential unintended consequence of these mandates: non-discerning auditors emerge to serve clients with low endogenous demand for auditing.[6]

2. Theoretical Framework and Prior Literature

[5] For example, the mixed findings surrounding whether the Big N auditors provide higher quality audits may be confounded by more than just which clients choose a Big N auditor (e.g., Lawrence et al., 2011): Big N auditors also choose which clients they accept. Our results suggest a more complete model of the two-sided match to better understand this issue. See, for example, Li, McNichols, and Raghunandan (2018).

[6] As an example, Figure 1 provides a website screenshot for an auditor with a large concentration in high misconduct BD clients. The website advertises low prices, a quick turnaround time, and a liberal client acceptance policy.

In studying auditor-client relationships, the literature focuses on several client preferences over auditors, such as auditor size, industry specialization, or reporting habits. In terms of size, clients seek auditors with sufficient labor and capital to conduct the audit, remain independent, and accept any litigation risk (DeAngelo, 1981; Dye, 1993; Lennox, 1999). Clients may prefer an auditor with industry expertise (Hogan and Jeter, 1999; Gerakos and Syverson, 2015; Bleibtreu and Stefani, 2017). In a recent study, Brown and Knechel (2016) find that clients of the same auditor have similar text in their 10-K disclosures, and argue that "the extent to which companies have similar audit preferences will cause them to choose a similar auditor" (p. 728). Additional research finds that companies relying on public financing or accessing the public markets for the first time are more likely to seek a reputable auditor because public capital providers lack private information about the firm and are poorly positioned to monitor it (Weber and Willenborg, 2003; Mansi, Maxwell, and Miller, 2004; Pittman and Fortin, 2004; Bills and Jensen, 2010).

A client's preference for a reputable auditor can also strengthen the *auditor's* preferences for reputable clients. Recent literature arguing that audits are a credence good illustrates this point (Causholli and Knechel, 2012). A credence good is one in which quality is unknown to the buyer, even after consumption, due to producer-consumer information asymmetries (Darby and Karni, 1973). For example, many medical services are credence goods because the patient lacks the expertise to evaluate the quality of the care provider ex-ante or the effectiveness of their treatment ex-post. In the case of audits, clients cannot readily observe the extent or quality of work performed as this work takes place. Absent an obvious ex-post audit failure (e.g., revelation of fraud linked to weak internal controls), the client may still lack the ability to assess the quality of the audit after it was performed.

In credence good markets, consumers often rely on a producer's reputation to help evaluate service quality to mitigate information asymmetry problems. As Baiman (1990) explains "if a contract between the two individuals could be written on their verifiable action choices, then there would be no need for reputation." (p. 356). The central hypothesis of our paper is that an auditor's reputation is in part formed by its client portfolio—auditors are known by the companies they keep. Producers with a reputation for providing high quality services to high quality clients can, in turn, charge a premium (Klein and Leffler, 1981; Bell, Landsman, and Shackelford, 2001; Donelson, Ege, and Leiby, 2019).

Since DeAngelo's (1981) canonical work, the literature has focused on how the existence of quasi-rents creates an incentive for auditors to deliver audit quality and maintain their reputation (e.g., Becker, DeFond, and Jiambalvo, 1998; Keune and Johnstone, 2012). However, DeAngelo also discusses how an auditor's quasi-rents provides them with "an incentive to design their client portfolios" (p. 197). While DeAngelo was concerned with the issue of auditor independence, her argument broadly applies to the auditor's overall portfolio strategy: quasi-rents will discipline client acceptance and continuance decisions. For our purposes, auditors whose clients have strong reputation preferences face the strongest incentives to screen—to decline new clients with track records of misconduct and separate from existing clients with such records. We expect high misconduct clients to instead match with auditors not participating in reputation-sensitive markets.

Empirical evidence on auditors' portfolio management decisions can be organized into two broad areas. One area seeks to understand how auditors manage litigation risk resulting from client reporting issues. Pratt and Stice (1994) conduct an experiment involving audit partners of Big N audit firms, and find client-related risks are positively associated with partners' assessments of litigation risk, which are in turn positively associated with audit effort and fee recommendations. Venkataraman, Weber, and Willenborg (2008) and Li et al. (2018) study audit quality issues surrounding IPO clients. Research also examines auditor portfolio changes following Sarbanes-Oxley (Landsman, Nelson, and Rountree, 2009) and AS5 (Schroeder and Hogan, 2013) and suggest that these changes reflect shifts in auditor preferences for misreporting risk.

A second area focuses on a broader set of reputation and engagement planning issues, primarily using experimental and field methodologies. Johnstone (2000) conducts an experiment and finds that audit partners are more inclined to manage client risk by avoiding risky clients than by adapting to the risks the clients present. Bell, Landsman, and Shackelford (2001) access survey data from a large audit firm, and report that auditors adapt to client-related risks by billing for additional effort. Johnstone and Bedard (2001, 2003, 2004a, 2004b) use internal data from a large audit firm, and develop models of portfolio management decisions, including those relating to risk assessment and response for auditors' client acceptance and continuance decisions, pricing, and audit effort planning. Lyon and Maher (2005) study 82 clients in the pre-Foreign Corrupt Practices Act era, and find those paying bribes in developing countries pay higher audit fees.

Collectively, research on litigation risk and client reporting issues finds that auditors are strategic in decisions about pricing, personnel resource allocation, and portfolio management. Other work finds similar strategic behavior on the part of auditors surrounding issues of reputation risk. However, this work is limited to small sample field work studying large auditors. As a result, the extent, importance, and consequences of auditor screening based on client reputation to the audit market as a whole are not well understood. Our subsequent sections describe the audit market we study and the matching framework we employ to investigate our predictions surrounding auditor reputation.

3. Setting, Data, and Summary Statistics

3.1 Setting: Broker-Dealers in the US

We study auditor-client relationships in the US broker-dealer market. Brokers execute securities transactions for their customers, whereas dealers execute securities transactions for themselves. When selling a proprietary holding to a customer, the entity is acting as both a broker and a dealer. Because brokers and dealers participate in the same market for investors and the literature studies them as a group, we follow the convention and study brokers and dealers together.

BDs deal in a variety of investment products, including exchange-traded equities, debt, options, variable life insurance, mutual funds, mortgage backed securities, and other securities. They can trade on the floor of the exchange, transact in privately-placed securities, or underwrite and create markets for securities. BD customers range from individual households to large institutional investors. In 2017, BDs executed over $42 trillion of transactions and generated over $308 billion of revenue (FINRA, 2018). That year, there were 3,726 BDs in the US employing over 630,000 FINRA-registered advisers.

BDs are regulated by the SEC under Rule 17a-5 of the 1934 Act. BDs are required to submit audited annual reports, which identify the auditor. BD audits provide reasonable assurance that the financial statements and required regulatory calculations are fairly stated, in all material respects, in conformity with US GAAP.[7] In 2017, there were 431 BD auditors with 690 offices. Audit firm sizes range from sole proprietors to Big N firms.

The SEC delegates some of its oversight to FINRA, a self-regulatory enforcement agency tasked with protecting investors in the US securities industry. In this role, FINRA oversees firm and adviser licensing, writes and enforces rules, and performs periodic examinations. To facilitate industry transparency, FINRA compiles and publicly reports customer complaints and adviser infractions in its BrokerCheck database. This database is the source of our misconduct and employment data.

3.2 Data and Summary Statistics

We construct our sample using the intersection of two datasets. Audit Analytics' BD database compiles company, financial statement, and audit report information from EDGAR between 2001 and 2017. As BDs are not required to report their audit fees, we do not have audit fees for the overwhelming majority of our sample.

[7] See Bedard et al. (2014) and Kowaleski et al. (2018) for detailed discussion of mandatory regulatory capital calculations, reporting requirements, and attestation.

For misconduct records, we turn to FINRA's BrokerCheck database of individuals employed by BDs. In January 2018, we accessed BrokerCheck's database of BD adviser records. The database contains all registered advisers currently employed in the US securities industry, as well as individuals employed up to ten years prior.[8] Each record contains information about the individual's current employment, previous employment, exams passed, state licenses, as well as disclosures of customer complaints, arbitrations, regulatory actions, employment terminations, bankruptcy filings, and any civil or criminal proceeding involving them. Figure 2 contains an example report from an individual in our sample. We aggregate the 1,228,778 adviser records in our sample to the BD-year level using the firm's unique central registration database number.

Table 1 details the construction of our sample using the Audit Analytics and FINRA data. Accessing all available Audit Analytics records between 2001 and 2017 yields 83,827 observations. Following Kowaleski (2018), we identify and remove 2,551 incomplete filings, and 3,561 filings with duplicate balance sheet, audit report, or attestation report variables, leaving us with 77,715 observations. After eliminating 1,763 observations missing FINRA data, 1,169 observations from foreign BDs, and 375 missing leverage, we arrive at our final sample of 74,408 BD-years.[9] For our main tests studying only new auditor-client relationships and requiring lagged variables (Tables 3-5), we have 6,894 BD-years. Table 2, Panel A presents summary statistics for the BD variables used in our analysis. The mean (median) *Total Assets* is \$1.00B (\$0.56M). We measure *Leverage* as the ratio of *Total Liabilities* to *Total Assets* and find that the mean ratio is 0.30.

[8] Following Egan et al. (2019), we use the term "financial adviser" and "adviser" interchangeably to refer to all FINRA-registered brokers, including those that are also registered investment advisers. Our main results are the same if we only consider the post-2007 period, where we observe the population of advisers, including those who subsequently exited the industry.

[9] We use the applicable SEC filing number or the BD's name to merge these files. Although the SEC requires each registered BD to annually file an audited report as if it were an independent entity, a number of BDs are affiliated with each other. We use Audit Analytics to identify BD affiliates on four dimensions: matching across parent ticker, parent name, parent CIK, and both address and auditor. We include affiliates in our analysis because affiliates often choose different auditors than one another, and because misconduct differs across affiliates. Nevertheless, when we drop all affiliates, we find the same results.

The average *BD Adviser Count* is 155. Seven percent of BDs are subsidiaries of publicly traded companies. We categorize twenty percent of BDs as carrying type BDs—those maintaining custody of ("carrying") investors' assets, while 48% are retail-focused.[10] The average BD firm age is 13.86 years. At the typical BD, the average adviser has 14.46 years of experience and has passed 2.12 of the six most common qualification exams (Series 6, 7, 24, 63, 65, and 66). The median growth in assets (advisers) is 2% (0%).

Panel B describes our audit variables. Nineteen percent of BDs have a *Big N* auditor, defined as the Big 4 plus Arthur Andersen. Five percent (2%) of BDs have an *IC Material Weakness (Going Concern* opinion). The typical audit office (defined as the intersection of an Auditor Name and an Opinion City in Audit Analytics) has 19.72 BD clients.[11] We observe audit offices with as few as one and as many as 144 clients in a year.

Panel C presents summary statistics for our misconduct measures, based on Egan et al. (2019). Egan et al. classify six out of the 23 types of disclosures on advisers' records as relating to misconduct: Civil-Final, Criminal-Final Disposition, Customer Dispute-Award/Judgment, Customer Dispute-Settled, Employment Separation after Allegations, and Regulatory-Final. Appendix B provides a definition and example for each misconduct disclosure type. For each adviser each year, we create an indicator for whether they have any misconduct that year, and an indicator for whether they had any misconduct on their record to date (i.e., this year or prior years, including with other employers). Then for each BD-year, similar to Egan et al. (2019) we take the average of each indicator across all of the BD's current advisers.

[10] BDs must maintain at least $250,000 of Net Capital if they have custody of customer assets or clear trades. We define retail BDs as those where the typical adviser is registered in more than three states, following Qureshi and Sokobin (2015) and Honigsberg and Jacob (2018).

[11] We use the terms "audit office", "office", and "auditor" interchangeably throughout the paper to refer to individual audit offices. Our main results are the same if we conduct our analysis at the auditor level, or if we eliminate auditors with more than one office.

At the typical BD, 1% of advisers are involved in misconduct in the current year (*BD Misconduct Current*), while 12% have been involved at any point in their career (*BD Misconduct Ever*). We observe many BDs—including dozens with over 100 advisers—with not one single adviser with a misconduct record. For example, State Employees' Credit Union Brokerage Services (560 advisers), and Rothschild, Inc. (164 advisers) have zero advisers with a misconduct record. Other BDs have large concentrations of advisers with misconduct records. In terms of all types of incidents (which encompass the six types of misconduct events plus less serious infractions and dismissed complaints) 2% (15%) of the average BD's advisers have a current (prior) disclosure.

4. Tests and Results

4.1 Auditor-Client Matching by Size and Misconduct

We begin with non-parametric analyses to provide an initial assessment of the auditor-client match. In Table 3, Panel A, we partition auditor-BD pairs into terciles based on the size of the BD and the average size of the auditor's BD clients, both measured in the year before they matched. Measuring size with a lag relative to the match year ensures that our auditor size and BD size tercile assignments are not mechanically correlated. We form terciles rather than study raw figures in order to facilitate comparisons across size and misconduct characteristics.[12] A quantile-based approach offers the additional advantage of reducing the influence of outliers on our results (in our sample, there is considerable skewness in both client size and client misconduct).

Our analysis involves three steps. First, we assign BDs to terciles each year according to their *Adviser Count* last year, with tercile 1 being the smallest and tercile 3 being the largest (*BD Size Tercile*). Second, for each BD, we assign their *auditor* to a size tercile (*Auditor Size Tercile*),

[12] We choose terciles rather than a larger number of quantiles to ensure a sufficient number of observations in each quantile each year. Nevertheless, our main results are the same using quartiles or quintiles.

based on the average size tercile of the auditor's BD clients.[13] Our choice to define an auditor based on the size of their clients rather than on their own size is motivated by our matching hypothesis that clients match with auditors who deal with clients similar to them. Regardless, we arrive at similar conclusions if we define auditors based on their own size (e.g., client count, or Big N auditor vs. rest). Third, we include only the first year of each BD-auditor relationship, such that we assess the importance of size in the year of the "match." Using this approach, the number of small, medium, and large BDs is 2,370, 2,240, and 2,284, while the size distribution across offices is 2,377, 2,242, and 2,275, respectively.

This simple non-parametric approach allows us to gauge the degree to which BDs and auditors match on size, and provides a benchmark for studying other characteristics (e.g., Berger, Minnis, and Sutherland, 2017). For example, the bottom row of Panel A shows the probability of each match type under the null hypothesis that size is not relevant to matching. Based on our size classifications, the null hypothesis is that 34.5% of BDs (regardless of their own size) match with small auditors, 32.5% with medium auditors, and 33.0% with large auditors. These probabilities are calculated as the frequencies of each auditor size tercile within the sample of all new relationship observations not missing controls or lagged variables.

However, actual matches do not follow the null pattern. For the smallest BDs (tercile 1), 48.8% match with an auditor focusing on small clients; compared to 34.5% focusing on medium-sized clients and just 16.7% focusing on large clients. We uncover a similar pattern for medium (tercile 2) and large (tercile 3) BDs: BDs most often match with auditors concentrated in their size tercile. Opposite matches ("mismatches") are particularly rare: large BDs are least likely (18.2%) to match with small client auditors, just as small BDs are least likely to match with large auditors

[13] Assigning BDs to each size tercile based on Total Assets produces similar evidence, as shown in Table A1 of our online appendix.

(16.7%). The Pearson's chi-squared test reported at the bottom of the panel rejects the null hypothesis of independence in BD size tercile and auditor size tercile at the 1% level.

We then perform a similar exercise (again for only new relationships, and lagging BD and auditor characteristics), but for misconduct rather than size. We focus on *BD Misconduct Ever*, for two reasons. First, as Table 2, Panel C shows, misconduct events are rare, and counting only events occurring within the year drastically restricts the across-BD variation we can document. Second, there is considerable persistence in misconduct at the individual level: Egan et al. (2019) report that prior offenders are five times as likely as the average adviser to engage in new misconduct.

To conduct the analysis, we first assign BDs to misconduct terciles *within* their size tercile (i.e., relative to their peers in *BD Size Tercile* 1, 2, or 3) in the previous year (*BD Misconduct Tercile*). We partition within BD size tercile since size may be correlated with misconduct, e.g., perhaps because BDs known for misconduct experience difficulty growing. Additionally, because our measure is based on the percent of a BD's advisers with a misconduct record, the distribution of this measure will differ between small BDs with few advisers and large BDs with many. We then assign auditors to misconduct terciles based on the average misconduct terciles of their clients in the previous year (*Auditor Misconduct Tercile*).

Table 3, Panel B presents the results. The bottom row shows the null hypothesis for each match type: 30.8%, 37.8%, and 31.5% for matches with low, medium, and high misconduct auditors, respectively. We would expect such matching rates if auditors did not care about misconduct that presents scant litigation risk, or if auditors do care but simply price reputation risk rather than turn away badly behaving clients.

In terms of actual matches, we find a similar, though less pronounced matching pattern compared to Panel A.[14] BDs tend to match to an auditor belonging to the same misconduct tercile

[14] As panels C and D of Table A1 show, we find misconduct matching if we separately study auditors who serve publicly held clients and those who do not.

or a neighboring tercile. Opposite matches occur infrequently, with the least common of all matches being the high misconduct BD-low misconduct auditor pair. The 11.2% (30.7% - 19.5%) deviation from the null for that particular pair is statistically and economically larger than the 4.1% (31.5% - 27.4%) deviation for the low misconduct BD-high misconduct auditor pair.

While our non-parametric approach provides useful initial evidence, we conduct a series of more rigorous analyses in Table 4, in which we control for a variety of potential confounding variables. We begin with the following OLS specification:

$$y_{i,t-1} = \beta_1 \times BD\ Misconduct_{i,t-1} + \alpha_{c,t-1} + \alpha_{r,t-1} + \alpha_{s,t-1} + \gamma \times Controls_{i,t-1} + \varepsilon_{i,t-1}, \tag{1}$$

where the unit of observation is BD-year. Because we are interested in the match between BDs and auditors, we restrict our sample to the first year of each BD-auditor pair in our sample. $y_{i,t-1}$ measures either the continuous auditor misconduct variable, the average rate of *Misconduct Ever* across the auditor's clients, or the quantile variable, *Auditor Misconduct Tercile*, assigned in Table 3.[15] We measure BD Misconduct using either the continuous variable, *Misconduct Ever*, or the quantiled variable, *BD Misconduct Tercile*, assigned in Table 3. Both misconduct variables are measured the year *before* BD *i*'s relationship with their auditor forms. We consider terciles in addition to continuous measures because the distribution of *Misconduct Ever* varies considerably across BD size groups, and we do not want non-linearities in the data to spuriously generate our result. Studying terciles also makes it easier to categorize matches (as in Table 3) and examine the relationship length of different categories of matches (as in Table 7, discussed below).

$\alpha_{c,t-1}$, $\alpha_{r,t-1}$, and $\alpha_{s,t-1}$ are carrying firm type x year, FINRA district x year, and *BD Size Tercile* x year fixed effects. These fixed effects allow us to absorb trends in audit relationships

[15] We arrive at the same inferences if we instead model BD misconduct as a function of auditor characteristics.

within BD business type (carrying or not), district, and size tercile, as well as general economic conditions and auditing standards that are constant within a year.[16]

In addition to these fixed effects, we also employ a set of controls (all lagged) for audit and BD characteristics. Our audit controls include indicators for whether the BD has an IC material weakness or going concern opinion (*IC Weakness*; *Going Concern*), and ownership type (*Publicly Held BD*). Our BD controls include the BD's *Leverage*, average adviser experience (*Log Average Adviser Experience*), and the average number of qualifications for advisers (*Average Qualifications*). We also control for BD age (*Log BD Age*), and business model (*Retail BD*). Although we control for *BD Size Tercile* x year fixed effects, we also include *Log Total Assets* and *Log BD Adviser Count* in our regressions, to ensure we are isolating the roles of size and misconduct in auditor-BD matching. Last, we control for BD growth in assets and advisers (*Asset Growth* and *Adviser Growth*). We cluster our standard errors at the audit office level; clustering instead by auditor does not affect our inferences.

A key advantage of our OLS specification is that it permits us to easily interpret coefficient magnitudes and assess the contributions of size and misconduct to matching. Additionally, compared to non-linear models occasionally employed in auditor choice research (e.g., logit), OLS better accommodates a large set of fixed effects that account for time-varying characteristics associated with the BD's size, type, and location, thus strengthening our ability to isolate the role of misconduct in matching.

As with the previously discussed nonparametric tests, we begin our regression analyses by first examining size-based matching as a benchmark. Table 4, Panel A, column 1 is a log-log specification in which we regress the number of advisers at an auditor's median client on the number

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[16] The 11 districts include San Francisco, Los Angeles, Denver, Kansas City, New Orleans, Dallas, Atlanta, Chicago, Philadelphia, New York, and Boston. See http://www.finra.org/industry/finra-district-offices for district definitions. We use districts rather than states because 30% of BD-auditor pairs are not in the same state.

of advisers at the BD. We use equation (1) but omit our controls for *Log Total Assets* as well as our BD size tercile x year and carrying firm type x year fixed effects. Doing so facilitates a comparison between the effects of changes in size (*Log BD Adviser Count)* and changes in misconduct (*Log BD Misconduct Ever)*. Column 1 shows a significantly positive relation between *Log BD Adviser Count* and *Log Auditor Median Client Size*. Column 2 replaces the size dependent variable with misconduct and finds a positive relation between a BD's misconduct and the misconduct profile of their auditor. To assess the economic magnitudes of the results in columns 1 and 2, we examine the relative change in the dependent variables for a one standard deviation change in the independent variables of interest and find that misconduct is 43% as important as size in explaining matches.[17] Thus, while size constraints are first order (a one-person audit firm lacks the resources to accept the largest BD), misconduct appears to play an economically important role in the formation of audit relationships.

Column 3 presents the results from estimating specification (1) with the full set of controls and fixed effects. We refer to this as our main result hereafter. We find a positive and significant relation between the BD's misconduct tercile and the auditor's misconduct tercile. The 0.098 coefficient implies that a one unit increase in the BD's misconduct tercile (e.g., from *Misconduct Tercile* 1 to 2 or 2 to 3) is associated with a 0.098 unit increase in the *Auditor Misconduct Tercile*.

We also investigate auditor-client matching using a multinomial logit regression (MLR) model, which is equivalent to structural estimators employed in the matching literature (e.g., Akkus, Cookson, and Hortacsu, 2015) under the assumption that the unobservables are independently distributed as type-1 extreme value. In this model, each BD is matched to the audit office providing the best match of all potential auditors, under a revealed preference assumption. This setup allows

[17] A one standard deviation increase in BD misconduct (size) is associated with a 0.111 (0.259) standard deviation increase in auditor misconduct (size), and 0.111/0.258=0.43.

us to test whether certain variables affect the probability of matching while considering other feasible matches. We define feasible matches based on the BD's ownership, whether they carry customer funds, and business model. Specifically, the MLR model assumes that publicly held BDs, carrying BDs, and retail BDs can only match with auditors currently dealing with publicly held BDs, carrying BDs, and retail BDs, respectively. We assume that privately held BDs, non-carrying BDs, and non-retail BDs can match with any auditor subject to the aforementioned constraints. Because we compare actual and feasible matches for the same BD at a point in time, our specification accounts for time factors and BD unobservables that could otherwise confound our analysis.

We study how the likelihood of a match depends on the absolute differences in the BD's and auditor's size (using *Log Adviser Count*) and misconduct profile (using the *Misconduct Ever* rate), as well as the geographic distance between them (using the square root of miles between the BD's location and the relevant audit office).[18] Studying differences as opposed to separate auditor and BD characteristics allows us to directly test whether BDs match to auditors with clients having similar features to them. Appendix C provides a full overview of this estimation.

Our results are presented in Table 4, Panel B. We find that differences in size and misconduct, as well as geographic distance have a statistically significant effect on the probability of matching. Economically, a one standard deviation increase in the difference between BD and auditor size (misconduct) reduces the odds of a match by 28% (20%). These estimates suggest that, controlling for BD business model features, misconduct is more than 70% as important as size in explaining matching—a magnitude in line with our Panel A estimation. In terms of distance, the 0.137 coefficient implies that each additional 100 miles between a BD and auditor reduce the odds of matching by 75%. Column 2 splits the misconduct difference variable according to whether the

[18] We lack distance information for several hundred observations; therefore, our sample is slightly smaller than the Table 3 and Table 4, Panel A samples.

BD or auditor has higher misconduct. We find that matching is roughly equally less likely when the auditor has higher misconduct than the BD and vice versa.

Our MLR specification offers several advantages over approaches used in structural estimation. First, the MLR enables interpretation of the magnitude of the coefficients in terms of the effect on the odds of matching. Second, MLR does not require an assumption on the bounds for possible coefficient values (as is required for the maximum score estimator used by Akkus et al., 2015) Third, our MLR estimation uses all observations rather than a randomly chosen subset (as is required in Akkus et al., due to computational complexity). Nevertheless, in Table A2 we repeat our analysis using structural estimators based on Logan, Hoff, and Newton (2008) and Akkus et al. We arrive at the same inference: client misconduct is important to explaining auditor-client matching.

Overall, we find consistent evidence of misconduct matching across four approaches (non-parametric analysis in Table 3, a linear regression studying misconduct rates and misconduct terciles in Table 4 Panel A, a matching regression in Table 4 Panel B, and structural estimation in Table A2). These specifications suggest that misconduct is between 40% and 70% as important as size in explaining matching. Our misconduct matching finding is unlikely to be driven by size, because we (a) form BD misconduct terciles *within* BD size terciles, (b) control for BD size tercile x year fixed effects, (c) control for total assets and adviser count in our regression, (d) find misconduct matching within each size tercile (discussed below), and (e) uncover misconduct matching in tests not relying on terciles to proxy for size or misconduct.

4.2 Robustness and Generalizability Analyses

We conduct a series of robustness tests in Table A3 of the appendix to verify our main findings. We begin by investigating the concern that the relation between auditor and BD misconduct is generated from an omitted variable associated with the BD's business model. For example, BDs are undergoing business model changes when they match with their auditor, as prior literature has linked auditor switches to management turnover and client performance (Schwartz and Menon, 1985; Johnson and Lys, 1990; DeFond, 1992). Yet another concern is that some BD product offerings may attract more misconduct complaints than others, and auditors may specialize in certain product offerings. Then, our results would reflect specialization in product offerings by auditors, rather than misconduct matching.

We address these concerns in two ways. First, we study a subsample of auditor switches instigated by the BD's prior auditor exiting the BD market, similar to the approach of Blouin, Grein, and Rountree (2007). These exits force the BD to find a new auditor, and we study whether their new auditor's clients have a similar misconduct profile to them. We construct our subsample using the set of audit offices with at least three BD clients last year, and none this year. We find 113 (79) audit office (audit firm) exits fit these criteria, leaving 513 BD clients to find new auditors.[19] Exits occur for a range of reasons, including the death of a sole proprietor, the demise of Arthur Andersen, and disciplinary action from the SEC or PCAOB. These audit market exits affect clients of all districts, sizes, ownership types, and in all years. We estimate specification (1) on this sample in column 1. We find a positive relation between a BD's misconduct and that of their new auditor's clients.

Second, we collect information, when available, on the BDs' types of product offerings that generate more than one percent of their annual revenue as indicated on SEC Form BD. Adapting Graham (2015), we create an indicator variable for each of the following six product offerings: Debt Security, Investment Advisory, Mortgage Backed Securities, Mutual Fund Retailer, Private Placement, and Variable Life Insurance and Annuity Dealer. We then interact these indicators with year fixed effects, such that our specification accounts for time-varying conditions in each product market and their effect on BD-auditor matches. Column 2 shows that our results remain when we

[19] We eliminate cases where over two-thirds of the exiting audit firm's clients flock to the same new auditor, to ensure we are not capturing acquisitions rather than exits.

control for product group x year fixed effects, indicating that product specialization is not behind our findings. Our results also remain if we run our tests separately for retail and non-retail BDs or BDs who sell investment advice and those who do not, or if we add a product offering dimension to our MLR specification.

We then examine the sensitivity of our results to alternative misconduct measures. Many misconduct disclosures result from customer complaints, and customers may not report all incidents given their own awareness of, or willingness to use, FINRA's complaint filing process. Because BDs differ in the types of customers they serve, two BDs with identical misconduct behavior may have different *reported* misconduct if they serve different customer types. We therefore assign BDs and auditors to terciles based only on regulator-reported misconduct, because we expect regulators to be more consistent in reporting misconduct across our BDs. Column 3 shows our results are statistically and economically similar to our original results. Column 4 counts all disclosure events on the adviser's record, rather than just the serious incidents classified as misconduct by Egan et al. (2019). Our results remain. Column 5 considers the current rate of misconduct at BDs, and finds similar results. Overall, it does not appear that our misconduct matching inference is sensitive to accounting for investment product specialization or to the type of misconduct incidents we consider.

Although adviser misconduct is separate from the financial reporting process, we adjust our design to further reduce the potential for litigation risk to explain our matching findings. In Table 5, Panel A we study a narrower misconduct set and BD clients with inherently low fraud risk. Column 1 forms BD and auditor misconduct terciles after omitting events plausibly informative about the likelihood of fraud. Specifically, we perform a textual analysis of our 1,228,778 adviser records, and omit criminal disclosures, instances where allegations led to employee separation from a previous employer, as well as disclosures containing the phrases "fraud", "forgery", “misappropriate”, “unregistered”, or variants of these phrases. The remaining disclosures (approximately 70% of the original sample) primarily relate to unsuitable investments, misrepresentation, unauthorized activity, and commission-related complaints. If litigation risk is solely responsible for our main results, then we expect much weaker or null results when we study these remaining disclosures. However, our results are statistically and economically similar to our main result.

Column 2 continues with this modified misconduct measure, and omits several types of BD-year observations where audit risk (and by extension, litigation risk) is expected to be greatest. Specifically, we exclude publicly held BDs, as well as BDs who maintain custody of their investors’ assets (“carrying BDs”) We also omit any BDs with IC material weaknesses or going concern opinions in the past or present. Last, we omit BDs with exposure to Mortgage Backed Securities. For the remaining observations, we expect litigation risk to be inherently low because the BD is not public, does not encounter the regulatory complexity and misappropriation risk that comes with taking custody of clients’ assets, has not reported IC material weaknesses or going concern opinions, and does not participate in the riskiest investment products. Column 2 shows that for the remaining BD-year observations, our results are similar to our main findings. Thus, when auditors are making client acceptance decisions, they appear to consider how their reputation is affected by aspects of management behavior not pertaining to litigation risk.

Finally, Panel B evaluates the generalizability of our misconduct matching findings. We investigate the auditor and BD client pairs where misconduct matching is relevant. If the misconduct matching we document is not found in the larger BDs responsible for the majority of assets and employment in the industry, it would raise questions about the importance of our findings. However, Columns 1 and 2 show that we find results for both the largest and smallest set of BDs, indicating that misconduct matching is relevant to clients of a variety of sizes. Likewise, column 3 (publicly held BD sample) and 4 (privately held BD sample) show that our matching findings do not depend on ownership type.

We then extend our sample to all US public companies. To study the broadest set of companies possible, we use AAERs and quarterly earnings per share meet-or-beat measures to develop proxies for public company behavior that we expect to be relevant to auditors.[20] Of course, one limitation of this broader analysis is that we cannot disentangle the roles of reputation and litigation risk in matching.

We assign companies to terciles by industry-year according to their prior incidence of AAERs and meeting or beating analyst expectations, and estimate a modified version of specification (1).[21] Columns 5 and 6 find a positively significant relation between a public company's AAER and meet-or-beat history and the history of their auditor's other clients.

Overall, our findings present consistent evidence of misconduct matching based on auditor reputation concerns, and not just litigation risk. This matching is not an artifact of size, location, BD type, or investment product-specific developments, and our findings are not limited to privately held BDs or small BDs.

4.3 Misconduct Matching and Auditor Reputation

In this section, we investigate three ways in which auditor reputation concerns relate to the misconduct matching we document in our main results. We begin by studying whether auditors dealing with reputation-sensitive clients are more likely to ration high misconduct BDs, resulting in a lower misconduct profile for these auditors. To test this, we develop three auditor portfolio measures. First, *Bank Exposure* is an indicator equal to one for auditors with bank clients that year, both public and private. Second, *No Public Exposure* is an indicator equal to one for auditors with no publicly held clients that year. Third, we measure the audit office's exposure to IPO markets

[20] Our analysis is related to Raghunandan (2018), who accesses a dataset on federal agency penalties, and studies the relation between financial and non-financial misconduct in public companies.

[21] Specifically, we study only new auditor-client relationships, and measure firms' AAER and meet or beat history over the previous five years. Column 6 has fewer observations than column 5 because many firms do not have analyst coverage throughout the five year period. Our regression controls for log revenue, log total assets, sales growth, cash flow volatility, profit margin, return on assets, leverage, market-to-book, log market value, and log firm age.

using an indicator for whether the auditor has an IPO client this year or a surrounding year (*IPO Exposure*). We then model *Auditor Misconduct Tercile* as a function of these variables, as well as auditor district x year fixed effects and the controls from equation (1) averaged across the audit office's clients. The unit of observation is audit office-year.

Table 6 presents the results. The first column shows that the BD clients of auditors with bank clients have lower misconduct. The -0.263 coefficient implies that having a bank client is associated with a 0.263 unit reduction in the auditor's misconduct tercile. This result also supports our earlier inference that misconduct matching stems from reputation concerns rather than specialization. Under a specialization interpretation, auditors with other financial institution clients should be better able to serve high misconduct BDs.

Column 2 shows that when an auditor has publicly held clients, their average misconduct tercile is significantly lower. Column 3 finds an incremental effect for IPO exposure. That is, while we continue to find that auditors with publicly held clients have lower misconduct BD clients, those with IPO clients have yet lower misconduct BD clients. Column 4 includes all three auditor portfolio measures in one regression, and finds each is associated with BD client misconduct according to our predictions.

Column 5 limits the sample to audit firms with at least two offices, and adds an audit firm x year fixed effect. By studying variation in IPO exposure and client misconduct across offices of the *same audit firm*, this specification allows us to identify differential reputation preferences across offices and how these preferences affect client portfolios. Our assumption is that audit firms maintain client acceptance policies, but that individual offices and partners have some discretion in implementing the policy and this discretion relates to the nature of their client base. We continue to find a significant coefficient on *IPO Exposure* (albeit, a smaller coefficient than our original result, indicating that across-audit firm variation is an important factor). The coefficients on *Bank Exposure* and *No Public Firm Exposure* have the same sign as our column 4 results, but are not statistically significant at conventional levels. Overall, our evidence indicates that both audit firms and individual audit offices avoid high misconduct BDs when they have reputation-sensitive clients in non-BD markets.[22]

Our second tests study how misconduct relates to the length of BD-auditor relationships, to provide insight into auditors' continuance decisions. We estimate auditor-client relationship length as the number of years between the first and last appearance in our dataset for the auditor-client pair, such that each pair only appears once in the test. The average estimated length is 3.99 years; naturally, actual relationships last longer because we do not observe pre-2001 data. We model relationship length using OLS as a function of the BD-auditor misconduct match using specification (1), in two ways.[23] First, we measure the absolute difference between the BD's *Misconduct Ever* rate and the average rate for the auditor's clients (*Abs Difference in Misconduct*). Second, we create indicator variables for exact misconduct matches (i.e., *Match* 1_A,1_{BD}, *Match* 2_A,2_{BD}, and *Match* 3_A,3_{BD} pairs where the auditor and client both belong to tercile 1, 2, or 3) and mismatches (*Match* 1_A,3_{BD} and *Match* 3_A,1_{BD} pairs where the auditor is in tercile 1 and the client is in tercile 3, or vice-versa). We characterize the match as of the last year of the data for each relationship. Other types of pairs (matches between 2s and 3s or between 1s and 2s) form the holdout sample. Intuitively, our second specification allows us to measure whether exact matched pairs stay together longer and highly mismatched pairs separate sooner, relative to other pairs.

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[22] In untabulated analysis, we also find that the average distance between auditors and BDs is greatest for those auditors concentrating on high misconduct BDs. Under the assumption that auditor-BD information asymmetry is increasing in distance (e.g., Choi et al., 2012; Francis, Golshan, and Hallman, 2017), this suggests that auditors concentrating on high misconduct BDs do less screening, reinforcing our reputation interpretation.
[23] We arrive at the same results if we omit our fixed effects and estimate a Weibull proportional hazards model.

Table 7 presents the results. Column 1 shows a significantly negative relation between *Relationship Length* and *Abs Difference in Misconduct*. The coefficient on the latter variable implies a one standard deviation increase in the difference in BD and auditor misconduct rates being associated with a 0.22 year decrease in relationship length.

We then study our indicators for exact and mismatched pairs. Column 2 shows that relationships where the BD and auditor both belong to misconduct tercile 1 (2) last 0.736 years (0.387 years) longer than the holdout group. High misconduct BD-high misconduct auditor pairs have weakly longer relationships (the t-statistic on *Match* $3_A,3_{BD}$ is 1.35). Column 2 also shows that mismatched pairs dissolve sooner. Notably, the shortest of all relationships are those involving low misconduct auditors and high misconduct BDs (*Match* $1_A,3_{BD}$), who dissolve 1.010 years earlier than the holdout group. By comparison, high misconduct auditors and low misconduct BD pairs (*Match* $3_A,1_{BD}$) dissolve just 0.425 years earlier. The difference between the *Match* $1_A,3_{BD}$ and *Match* $3_A,1_{BD}$ coefficients is economically and statistically significant (p-value 0.05). This finding is consistent with low misconduct auditors declining continuance to high misconduct clients, either because these clients' misconduct behavior has not improved, worsened, or because the auditor learns about the client over the course of the engagement (Morgan and Stocken, 1998). This finding also complements our Table 3, Panel B evidence showing that *Match* $1_A,3_{BD}$ pairs are the least likely to form in the first place.

Column 3 adds indicators for each type of size match from Table 3, Panel A and finds similar results. Last, we address an omitted variable concern about variation in the availability of auditors in various parts of the country, which could explain why certain pairs last longer than others. Specifically, we control for the log number of auditors within 100 miles of the BD.[24] Our results remain.

[24] We are unable to calculate this variable for several thousand observations missing zip code data.

Our third tests in this section study how auditors respond to an improvement in transparency surrounding BD behavior. In 2006, Congress passed the Military Personnel Financial Services Protection Act, which required the expansion of publicly available information about the professional background and conduct of advisers. The information was made available by the National Association of Securities Dealers (a predecessor of FINRA) on the BrokerCheck website, detailed as follows (NASD, 2007; emphasis added):

> Today's launch marks the first major modernization of NASD BrokerCheck since the service was first introduced online in 1998. *The public disclosure program has been responding to written inquiries since 1988 and to telephone inquiries since 1990*. Beginning today, NASD BrokerCheck is available online 24 hours a day, seven days a week. Vastly improved search options make finding an individual broker or firm faster and easier. When they find that a broker or firm has "disclosure events" such as criminal actions, customer complaints and disciplinary actions by regulators, *investors no longer have to make a separate request for a disclosure report to be sent via email at a later time. Instead, the disclosure report is available online within seconds*.

Our assumption is that the website reform made it easier for auditors to evaluate client misconduct profiles, and had little effect on clients' ability to evaluate auditors.[25] This is because the website contained no auditor information, the Audit Analytics BD module we use was not yet available, and we are not aware of any other public dataset compiling BD auditor portfolio information around this time.

We study the composition of auditors' client portfolios around the March 2007 website modernization. If auditors differ in their tolerance of client misconduct, then we expect the availability of client misconduct information to increase auditors' portfolio concentration with respect to client misconduct. To assess this, we measure the standard deviation of misconduct rates (*Std Dev Client Misconduct*) across each audit office's clients each year.[26] We model this dispersion measure as a function of *Transparency* (an indicator equal to one after 2007), the controls from

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[25] Discussions with several audit partners in the BD market confirm that the website informs their acceptance and continuance decisions.

[26] We find similar results using the interquartile range as our dispersion measure.

equation (1) averaged across the office's clients, and office fixed effects. We limit our sample to the two years before and after 2007, to reduce the threat of other developments entering our results. We omit 2007 because we do not observe the exact timing of auditor-BD matches, just the year-end audit report date.

Table 8 presents the results. Column 1 shows a significant post-modernization reduction in portfolio dispersion. Considering the pre-period *Std Dev Client Misconduct* of 13.6%, our -1.5% coefficient implies an economically significant 11% decline in portfolio dispersion. Of course, one limitation of this particular analysis is that it relies upon a simple pre-post comparison around a single event. Specific to our setting, one might be concerned that our post period coincides with the onset of the financial crisis. To reduce this concern, column 2 adds time-varying controls for the office's exposure to clients participating in each of the six product offerings. Further, column 3 eliminates offices with any clients participating in the Mortgage Backed Securities market, which experienced considerable turmoil during the crisis. In both columns, we arrive at economically and statistically similar results.

4.4 Auditor-Client Matches and Future Misconduct

Our final set of tests sheds light on the consequences of misconduct matching for investor protection. Specifically, we examine whether a BD's auditor match is relevant to future misconduct. We study *BD Misconduct Current* (i.e., new misconduct incidents) in the years after auditor matches. We estimate future misconduct as a function of *High Misconduct Auditor*, equal to one for misconduct tercile 3 auditors, and zero for tercile 1 or 2 auditors. We also control for the BD's misconduct in the year before the match, and the controls and fixed effects from equation (1). The coefficient of interest is *High Misconduct Auditor*. A positive coefficient on this variable indicates worse future behavior after matching with a high misconduct auditor. A negative coefficient indicates the opposite, and would be more consistent with auditor specialization yielding oversight benefits. In a specialization story, those auditors with the most experience dealing with high misconduct clients should be best positioned to help new clients reform behavior and reduce misconduct.

Table 9 presents the results. Column 1 shows a positive coefficient on *High Misconduct Auditor*, indicating that those BDs matching with lower reputation auditors experience a higher rate of *BD Misconduct Current* over the next year. Considering only non-reporting misconduct (column 2), using a continuous measure of auditor misconduct (column 3), measuring future misconduct over the next two years (column 4), or adding a control for *BD Misconduct Ever* (column 5) does not affect the results. Column 6 repeats our test on high misconduct BDs—those who are tercile 3 BDs in the year before they match with their auditor. We find the same results for this sample: those BDs with a *High Misconduct Auditor* experience a significantly higher rate of misconduct over the next two years.

We caution that these tests are not intended to be interpreted causally. Specifically, prior work (e.g., Lawrence, Minutti-Meza, and Zhang, 2011) and our own main findings illuminate the challenges associated with identifying auditor treatment effects in the presence of matching. Nevertheless, we note that our findings are consistent with three non-mutually exclusive mechanisms involving auditors' heterogeneous preferences for reputation. First, because we control for public information about BD misconduct, our findings are consistent with high reputation auditors developing private information to screen potential clients (*screening*). Second, high reputation auditors, through their audit procedures and oversight of internal controls, could reduce the scope for BD misconduct (*treatment*). Third, those BDs intending to root out misconduct may seek to match with high reputation auditors (*selection*).

5. Conclusion

Research on auditor reputation has been hampered by limited data on the least reputable clients and auditors, as well as difficulties separating reputation from litigation risk. We examine the BD market, which allows us to observe employee misconduct that does not pertain to litigation risk, and study how it influences matching between the full set of auditors and clients. We find that a BD's past misconduct record is highly related to the misconduct record of their new auditor's clients. Auditors' involvement in other reputation-sensitive markets reduces their willingness to deal with high misconduct BDs. BDs and auditors that are mismatched with respect to misconduct stay together the least amount of time. Furthermore, once FINRA improved the transparency surrounding adviser misconduct, auditors increased their concentration in a given misconduct clientele. Our findings suggest that auditor reputation concerns contribute to selectivity in the clients they choose to accept and continue serving. Finally, we show that an auditor's portfolio misconduct rate is predictive of a BD's future misconduct behavior, over-and-above the BD's own historical misconduct level.

Our findings carry multiple implications for future research. First, work investigating auditor-client relationships or auditor treatment effects on clients should consider how auditor reputation concerns contributed to the match. For example, a finding of a lower cost of capital for clients of Big N auditors could reflect the extent of screening by Big N auditors, instead of (or in addition to) audit quality. Second, research on reputation should consider not only how auditors price business risk, but also the more fundamental question of which clients they accept versus turn away. Settings where one can observe the full set of auditors and clients, not just large auditors of public firms, are particularly suited for these endeavors. Third, in markets where auditor reputation is important, the identity of a client's auditor can be informative about the client's future behavior. And last, audit mandates can provide incentives for non-selective auditors to enter the market and serve clients with low endogenous demand for auditing.

One limitation of our setting is that we cannot observe the audit fees paid by BDs, or the fees that other auditors had quoted them. We encourage future research on how different auditors price engagements as a function of the client's reputation. A natural extension of this research would consider the client welfare effects of mandatory auditor rotation, auditor M&A, or the exit of an auditor from the market.

References

Abdulkadiroğlu, A., Pathak, P. A., & Roth, A. E. (2005). The New York City high school match. *American Economic Review*, *95*(2), 364-367.

Abdulkadiroğlu, A., Pathak, P. A., & Roth, A. E. (2009). Strategy-proofness versus efficiency in matching with indifferences: Redesigning the NYC high school match. *American Economic Review*, *99*(5), 1954-78.

Akkus, O., Cookson, J. A., & Hortacsu, A. (2015). The determinants of bank mergers: A revealed preference analysis. *Management Science*, *62*(8), 2241-2258.

Azevedo, E. M., & Leshno, J. D. (2016). A supply and demand framework for two-sided matching markets. *Journal of Political Economy*, *124*(5), 1235-1268.

Baiman, S. (1990). Agency research in managerial accounting: A second look. *Accounting, Organizations and Society*, *15*(4), 341-371.

Becker, C. L., DeFond, M. L., Jiambalvo, J., & Subramanyam, K. R. (1998). The effect of audit quality on earnings management. *Contemporary accounting research*, *15*(1), 1-24.

Becker, G. S. (1973). A theory of marriage: Part I. *Journal of Political Economy*, *81*(4), 813-846.

Bedard, J. C., Cannon, N.H, & Schnader, A.L. (2014). The changing face of auditor reporting in the broker-dealer industry. *Current Issues in Auditing*, *8*(1), A1-A11.

Bell, T., Landsman, W.R., & Shackelford, D.A. (2001). Auditors perceived business risk and audit fees: Analysis and evidence. *Journal of Accounting Research*, *39*(1), 35-43.

Berger, P. G., Minnis, M., & Sutherland, A. (2017). Commercial lending concentration and bank expertise: Evidence from borrower financial statements. *Journal of Accounting and Economics*, *64*(2-3), 253-277.

Bills, J. L., & Jensen, L. (2010). Auditor-Client Pairing: A Positive Assortative Matching Market. Working paper.

Bleibtreu, C., & Stefani, U. (2017). The effects of mandatory audit firm rotation on client importance and audit industry concentration. *The Accounting Review*, *93*(1), 1-27.

Blouin, J., Grein, B. M., & Rountree, B. R. (2007). An analysis of forced auditor change: The case of former Arthur Andersen clients. *The Accounting Review*, *82*(3), 621-650.

Brown, S. V., & Knechel, W. R. (2016). Auditor-client compatibility and audit firm selection. *Journal of Accounting Research 54*(3), 725-775.

Causholli, M., & Knechel, W. R. (2012). An examination of the credence attributes of an audit. *Accounting Horizons*, *26*(4), 631-656.

Charoenwong, B., Kwan, A., & Umar, T. (2019). Does Regulatory Jurisdiction Affect the Quality of Investment-Adviser Regulation?. In *Fifth Annual Conference on Financial Market Regulation*.

Chen, F., S. Peng, S. Xue, Z. Yang, and F. Ye. (2016). Do clients successfully engage in opinion shopping? Partner-level evidence. *Journal of Accounting Research*, *54*(1), 79-112.

Chib, S. & Greenberg, E. (1998). Analysis of multivariate probit models. *Biometrika*, *85*(2), 347-361.

Choi, J. H., Kim, J. B., Qiu, A. A., & Zang, Y. (2012). Geographic proximity between auditor and client: How does it impact audit quality?. *Auditing: A Journal of Practice & Theory*, *31*(2), 43-72.

Coffee, J. C. (2019). Why do auditors fail? What might work? What won't?. *Accounting and Business Research*, *49*(5), 540-561.

Darby, M. R., & Karni, E. (1973). Free competition and the optimal amount of fraud. *The Journal of law and economics*, *16*(1), 67-88.

Davidson, R., Dey, A., & Smith, A. (2015). Executives "off-the-job" behavior, corporate culture, and financial reporting risk. *Journal of Financial Economics*, *117*(1), 5-28.

DeAngelo, L. E. (1981). Auditor size and audit quality. *Journal of accounting and economics*, *3*(3), 183-199.

DeFond, M.L. (1992). The association between changes in client firm agency costs and auditor switching. *Auditing: A Journal of Practice and Theory*, *11*(1), 16.

DeFond, M. & J. Zhang. (2014). A review of the archival auditing research. *Journal of Accounting and Economics*, *58*(2-3), 275-326.

Dimmock, S.G., & Gerken, W.C. (2012). Predicting fraud by investment managers. *Journal of Financial Economics*, *105*(1), 153–73.

Dimmock, S.G., Gerken, W.C., & Graham, N.P. (2018). Is fraud contagious? Coworker influence on misconduct by financial advisors. *The Journal of Finance, 3*, 1417–50.

Donelson, D. C., Ege, M., & Leiby, J. (2018). Audit Firm Reputational Consequences of Alleged Non-Accounting Misconduct by Clients. *Available at SSRN 2783523*.

Dye, R. A. (1993). Auditing standards, legal liability, and auditor wealth. *Journal of political Economy*, *101*(5), 887-914.

Egan, M. L., Matvos, G., & Seru, A. (2017). *When Harry fired Sally: The double standard in punishing misconduct* (No. w23242). National Bureau of Economic Research.

Egan, M., Matvos, G., & Seru, A. (2019). The market for financial adviser misconduct. *Journal of Political Economy*, *127*(1), 233-295.

FINRA. 2016, Investors in the United States. December 2016. Available at: https://www.finra-foundation.org/files/investors-united-states-2016. (Accessed March 7, 2019).

FINRA. 2018 FINRA Industry Snapshot. August 2018. Available at: *http://www.finra.org/sites/default/files/2018_finra_industry_snapshot.pdf*. (Accessed August 20, 2018).

Focarelli, D., Panetta, F., & Salleo, C. (2002). Why do banks merge?. *Journal of money, credit and banking*, 1047-1066.

Francis, J. R., Golshan, N., & Hallman, N. (2017). Out of Sight, Out of Mind: Does Audit Partner Proximity to Clients Matter?. *Out of Mind: Does Audit Partner Proximity to Clients Matter*.

Gale, D., & Shapley, L.S. (1962). College admissions and the stability of marriage. *The American Mathematical Monthly*, *69*(1), 9-15.

Gerakos, J., & Syverson, C. (2015). Competition in the audit market: Policy implications. *Journal of Accounting Research*, *53*(4), 725-775.

Glaeser, S., & Guay, W. R. (2017). Identification and generalizability in accounting research: A discussion of Christensen, Floyd, Liu, and Maffett (2017). *Journal of Accounting and Economics*, *64*(2-3), 305-312.

Graham, N. (2015). Brokers, advisors, and the fiduciary standard. Working paper.

Gurun, U.G., Stoffman, N., & Yonker, S.E. (2017). Trust busting: The effect of fraud on investor behavior. *The Review of Financial Studies*, *31*(4), 1341-1376.

Hao, L. 2008. Assortative Matching. In: Palgrave Macmillan (eds.) *The New Palgrave Dictionary of Economics*. Palgrave Macmillan, London.

Hogan, C. E., & Jeter, D. C. (1999). Industry specialization by auditors. *Auditing: A Journal of Practice & Theory*, *18*(1), 1-17.

Honigsberg, C. & Jacob, M. (2018). Deleting misconduct: The expungement of BrokerCheck records. Working paper.

Johnson, W., & Lys T. (1990). The market for audit services: Evidence from voluntary auditor changes. *Journal of Accounting and Economics*, *12*, 281-308.

Johnstone, K.M. (2000). Client-acceptance decisions: Simultaneous effects of client business risk, audit risk, auditor business risk, and risk adaptation. *Auditing: A Journal of Practice & Theory*, *19*(1), 1-25.

Johnstone, K. M., & Bedard, J. C. (2001). Engagement planning, bid pricing, and client response in the market for initial attest engagements. *The Accounting Review*, *76*(2), 199-220.

Johnstone, K.M., & Bedard, J.C. (2003). Risk management in client acceptance decisions. *The Accounting Review*, *78*(4), 1003-1025.

Johnstone, K. M., & Bedard, J. C., (2004a). Earnings manipulation risk, corporate governance risk, and auditors' planning and pricing decisions. *The Accounting Review*, *79*(2), 277-304.

Johnstone, K.M., & Bedard, J.C. (2004b). Audit firm portfolio management decisions. *Journal of Accounting Research*, *42*(4), 659-690.

Keune, M. B., & Johnstone, K. M. (2012). Materiality judgments and the resolution of detected misstatements: The role of managers, auditors, and audit committees. *The Accounting Review*, *87*(5), 1641-1677.

Kim, Y., & Park, M. S. (2014). Real activities manipulation and auditors' client-retention decisions. *The Accounting Review*, *89*(1), 367-401.

Klein, B., & Leffler, K. B. (1981). The role of market forces in assuring contractual performance. *Journal of political Economy*, *89*(4), 615-641.

Kowaleski, Z.T. (2018). Auditor size, partner-specialization, and private company audit adjustments: Insights from the broker-dealer industry. Dissertation, University of Wisconsin.

Kowaleski, Z.T., Cannon, N.H., Schnader, A.L., & Bedard, J.C. (2018). The continuing evolution of auditor reporting in the broker-dealer industry: Issues and opportunities. Current Issues in Auditing, forthcoming.

Krishnan, J., & Krishnan, J. (1997). Litigation risk and auditor resignations. *The Accounting Review*, *72*(4), 539-560.

Landsman, W. R., Nelson, K. K., & Rountree, B. R. (2009). Auditor switches in the pre-and post-Enron eras: Risk or realignment?. *The Accounting Review*, *84*(2), 531-558.

Law, K., & Mills, L. (2018). Do Financial Gatekeepers Under-Protect Investors? Evidence from Criminal Background Checks. Working paper.

Lawrence, A., Minutti-Meza, M., & Zhang, P. (2011). Can Big 4 versus non-Big 4 differences in audit-quality proxies be attributed to client characteristics?. *The accounting review*, *86*(1), 259-286.

Lennox, C. S. (1999). Audit quality and auditor size: An evaluation of reputation and deep pockets hypotheses. *Journal of Business Finance & Accounting*, *26*(7-8), 779-805.

Lennox, C. (2000). Do companies successfully engage in opinion-shopping? Evidence from the UK. *Journal of accounting and economics*, *29*(3), 321-337.

Lennox, C., & Li, B. (2014). Accounting misstatements following lawsuits against auditors. *Journal of Accounting and Economics*, *57*(1), 58-75.

Li, K., McNichols, M.F., & Raghunandan, A. (2018). A two-sided matching model of the audit market for IPO firms.

Liu, Q., Mailath, G. J., Postlewaite, A., & Samuelson, L. (2014). Stable matching with incomplete information. *Econometrica*, *82*(2), 541-587.

Logan, J. A., Hoff, P. D., & Newton, M. A. (2008). Two-sided estimation of mate preferences for similarities in age, education, and religion. *Journal of the American Statistical Association*, *103*(482), 559-569.

Lyon, J. D., & Maher, M. W. (2005). The importance of business risk in setting audit fees: Evidence from cases of client misconduct. *Journal of Accounting Research*, *43*(1), 133-151.

Mansi, S. A., Maxwell, W. F., & Miller, D. P. (2004). Does auditor quality and tenure matter to investors? Evidence from the bond market. *Journal of Accounting Research*, *42*(4), 755-793.

McKenna, F., & Riquier, A. (2017, August 21). Where was KPMG, Wells Fargo's auditor, while the funny business was going on? *MarketWatch*. Retrieved from www.marketwatch.com

Morgan, J., & Stocken, P. (1998). The effects of business risk on audit pricing. *Review of Accounting Studies*, *3*(4), 365-385.

NASD. (2007). New improved NASD BrokerCheck goes live online today. Available at: http://www.finra.org/newsroom/2007/new-improved-nasd-brokercheck-goes-live-online-today (Accessed September 28, 2018).

Newton, N., J. Persellin, D. Wang, and M. Wilkins. (2016). Internal Control Opinion Shopping and Audit Market Competition. *The Accounting Review*, *91*(2), 603-623.

Pacelli, J. (2018). Corporate Culture and Analyst Catering. *Journal of Accounting and Economics*.

Parsons, C. A., Sulaeman, J., & Titman, S. (2018). The geography of financial misconduct. *The Journal of Finance*, *73*(5), 2087-2137.

Pittman, J. A., & Fortin, S. (2004). Auditor choice and the cost of debt capital for newly public firms. *Journal of accounting and economics*, *37*(1), 113-136.

Pratt, J., & Stice, J. D. (1994). The effects of client characteristics on auditor litigation risk judgments, required audit evidence, and recommended audit fees. *Accounting Review*, 639-656.

Qureshi, H., & Sokobin, J.S. (2015). Do investors have valuable information about brokers?" SSRN Scholarly Paper. Rochester, NY: Social Science Research Network: https://papers.ssrn.com/abstract=2652535.

Raghunandan, A. (2018). Are Non-Financial and Financial Misconduct Complements?: Evidence From Federal Agency Penalties. *Evidence From Federal Agency Penalties (December 28, 2018)*.

Roth, A. E., & Sotomayor, M. (1992). Two-sided matching. *Handbook of game theory with economic applications*, *1*, 485-541.

Schnader, A.L., Bedard, J.C., & Cannon, N.H. (2018). Auditor Reporting and Regulatory Sanctions in the Broker-Dealer Industry: From Self-Regulation to PCAOB Oversight. Contemporary Accounting Research, forthcoming.

Schroeder, J. H., & Hogan, C. E. (2013). The impact of PCAOB AS5 and the economic recession on client portfolio characteristics of the Big 4 audit firms. *Auditing: A Journal of Practice & Theory*, *32*(4), 95-127.

Schwartz, K.B., & Menon, K. (1985). Auditor switches by failing firms. *The Accounting Review*, 248-261.

Shu, S.Z. (2000). Auditor resignations: Clientele effects and legal liability. *Journal of Accounting and Economics*, *29*(2), 173-205.

Skinner, D. J., & Srinivasan, S. (2012). Audit quality and auditor reputation: Evidence from Japan. *The Accounting Review*, *87*(5), 1737-1765.

Soltes, E. (2016). *Why they do it: inside the mind of the white-collar criminal*. PublicAffairs.

Venkataraman, R., Weber, J.P., & Willenborg, M. (2008). Litigation risk, audit quality, and audit fees: Evidence from initial public offerings. *The Accounting Review*, *83*(5), 1315-1345.

Weber, J., & Willenborg, M. (2003). Do expert informational intermediaries add value? Evidence from auditors in microcap initial public offerings. *Journal of Accounting Research*, *41*(4), 681-720.

Weber, J., Willenborg, M., & Zhang, J. (2008). Does auditor reputation matter? The case of KPMG Germany and ComROAD AG. *Journal of Accounting Research*, *46*(4), 941-972.

Willenborg, M. (1999). Empirical analysis of the economic demand for auditing in the initial public offerings market. *Journal of Accounting Research*, *37*(1), 225-238.

Appendix A: Variable Definitions

Variable	Description
BD Size Tercile	The size tercile (1=small, 2=medium, 3=large) of the BD. We assign BDs to terciles each year according to their number of advisers.
Auditor Size Tercile	The size tercile (1=small, 2=medium, 3=large) of the BD's auditor. We assign auditors to terciles each year according to the average size tercile of their BD clients.
BD Misconduct Tercile	The misconduct tercile (1=low, 2=medium, 3=high) of the BD. We assign BDs to terciles each year according to *BD Misconduct Ever*. These misconduct terciles are assigned within *BD Size Tercile*, to control for size.
Auditor Misconduct Tercile	The misconduct tercile (1=low, 2=medium, 3=high) of the BD's auditor. We assign auditors to terciles each year according to the average *BD Misconduct Tercile* of their clients.
Audit Office	The intersection of auditor name and opinion city in Audit Analytics.
Total Assets	The total assets reported at the end of the BD's fiscal year.
Leverage	The ratio of total liabilities to total assets reported at the end of the BD's fiscal year.
Adviser Count	The number of FINRA-registered advisers in the BD-year.
Publicly Held BD	An indicator equal to one for BD subsidiaries of publicly traded companies, and zero otherwise. We classify a BD as publicly traded if it has a ticker symbol in Audit Analytics.
Retail BD	An indicator equal to one for BDs that serve individual rather than institutional customers. Following Qureshi and Sokobin (2015) and Honigsberg and Jacob (2018), we classify BDs as retail when their average adviser is registered in more than three states.
Carrying Type	BDs that maintain custody of investors' assets. As public data does not identify these BDs, we follow Schnader et al. (2018) and create an indicator equal to one when Audit Analytics reports a Minimum Required Net Capital of at least $250,000, and zero otherwise.
BD Age	The number of years since the BD first appears in the FINRA data.

Average Adviser Experience	The average number of years of experience across the BD's advisers. We use the earliest year of FINRA registration for each adviser to calculate experience.
Average Adviser Qualifications	The average number of qualification exams passed by the BD's advisers. Following Egan et al. (2019), we consider the six most common qualification exams (Series 6, 7, 24, 63, 65, and 66).
Asset Growth	The percent change in Total Assets for the BD that year.
Adviser Growth	The percent change in Adviser Count for the BD that year.
Big N Auditor	An indicator equal to one for BD-years audited by PwC, EY, Deloitte, KPMG, or Arthur Andersen.
IC Material Weakness	An indicator equal to one if the BD has an internal control material weakness that year, and zero otherwise.
Going Concern	An indicator equal to one if the BD has a going concern opinion that year, and zero otherwise.
Audit Office Client Count	The number of BD clients for the audit office that year.
Auditors Near BD	The number of audit offices within 100 miles of the BD, computed using spherical trigonometry.
BD Misconduct Current	The percent of the BD's advisers with a misconduct event that year. We use the Egan et al. (2019) definition of misconduct, which includes the following six categories of FINRA disclosures: Civil-Final, Criminal-Final Disposition, Customer Dispute-Award/Judgment, Customer Dispute-Settled, Employment Separation after Allegations, and Regulatory-Final as described in Appendix B.
Non-Reporting Misconduct Current	The percent of the BD's advisers with a non-reporting misconduct event that year. From the BD Misconduct Current variable, we omit criminal disclosures, instances where allegations led to employee separation from the BD, as well as disclosures containing the phrases "fraud", "forgery", "misappropriate", "unregistered", or variants of these phrases.
BD Misconduct Ever	The percent of the BD's advisers with a misconduct event that year or any prior year.
BD Disclosure Current	The percent of the BD's advisers with a FINRA disclosure that year. Disclosures can include Misconduct events or less serious complaints and infractions (including those that were dismissed).

BD Disclosure Ever	The percent of the BD's advisers with a FINRA disclosure that year or any prior year.
Auditor Median Client Size	The number of advisers at the auditor's median client.
Auditor Misconduct Ever	The average *BD Misconduct Ever* rate across the audit office's clients.
Abs Difference in Misconduct	The absolute difference between *BD Misconduct Ever* and *Auditor Misconduct Ever*.
Abs Difference in Misconduct (BD Higher)	The *Abs Difference in Misconduct* when *BD Misconduct Ever* is greater than *Auditor Misconduct Ever*, and zero otherwise.
Abs Difference in Misconduct (Auditor Higher)	The *Abs Difference in Misconduct* when *BD Misconduct Ever* is less than *Auditor Misconduct Ever*, and zero otherwise.
Abs Difference in Size	The absolute difference between the BD's *Log Adviser Count* and the *Log Adviser Count* for the auditor's average client.
Distance	The distance (in miles) between the BD and the specific office of the auditor they engage, computed using spherical trigonometry.
No Public Exposure	An indicator equal to one if the audit office has no publicly held clients.
Bank Exposure	An indicator equal to one if the audit office has a bank client this year.
IPO Exposure	An indicator equal to one if the audit office has an IPO client last year, this year, or next year.
Relationship Length	The number of years between the first and last appearance in the data for the BD-auditor pair.
Match $\#_{A}$,$\#_{BD}$	An indicator equal to one for a pairs with an auditor from misconduct tercile # and a BD from misconduct tercile #. For example, Match 1_{A}-3_{BD} equals one for pairs with an auditor from misconduct tercile 1 and a BD from misconduct tercile 3.
Transparency	An indicator equal to one in year 2008 and 2009, and zero in year 2005 and 2006.
Std Deviation Client Misconduct	The standard deviation of BD Misconduct Ever across the audit office's clients.

High Misconduct Auditor	An indicator variable equal to one for BD-auditor pairs where the auditor belongs to the highest *Auditor Misconduct Tercile*, and zero when the auditor belongs to the lowest two *Auditor Misconduct Terciles*.
BD Regulator Misconduct Tercile	The regulator misconduct tercile (1=low, 2=medium, 3=high) of the BD. We assign BDs to terciles each year according to a variant of *BD Misconduct Ever* that considers only regulator-reported misconduct. These regulator misconduct terciles are assigned within *BD Size Tercile*, to control for size.
Auditor Regulator Misconduct Tercile	The regulator misconduct tercile (1=low, 2=medium, 3=high) of the BD's auditor. We assign auditors to terciles each year according to the average *BD Regulator Misconduct Tercile* of their clients.
BD Disclosure Tercile	The disclosure tercile (1=low, 2=medium, 3=high) of the BD. We assign BDs to terciles each year according to *BD Disclosure Ever*. These disclosure terciles are assigned within *BD Size Tercile*, to control for size.
Auditor Disclosure Tercile	The disclosure tercile (1=low, 2=medium, 3=high) of the BD's auditor. We assign auditors to terciles each year according to the average *BD Disclosure Tercile* of their clients.
Auditor Misconduct Current Rate	The average *BD Misconduct Current* rate across the audit office's clients.

Appendix B: Examples of Each Misconduct Type

This table provides definitions for each of the six misconduct categories, as well as example disclosures. In some cases, excerpts are provided for brevity. We have redacted the names of individuals and firms involved in the example misconduct disclosures.

Misconduct Category	**Example**
Civil-Final This type of disclosure event involves (1) an injunction issued by a court in connection with investment-related activity, (2) a finding by a court of a violation of any investment-related statute or regulation, or (3) an action brought by a state or foreign financial regulatory authority that is dismissed by a court pursuant to a settlement agreement.	The Securities and Exchange Commission ("Commission" or "SEC") today charged a California-based investment adviser and its owner with fraud for failing to disclose a material conflict of interest when recommending that their clients invest in a hedge fund that made undisclosed subprime and other high-risk investments. The SEC alleges that investment adviser company ("Company") and its Principal recommended that more than 60 of their clients invest approximately $40 million in equity options fund ("Fund"), a hedge fund managed by consulting firm ("Firm"). According to the SEC's complaint, Company and owner failed to disclose a side agreement in which company received a portion of the performance fee that fund paid firm for all the company assets invested in the hedge fund. From April 2005 to September 2007, the company received more than $350,000 in performance fees from the firm. The fund collapsed in August 2007, and company clients lost nearly all of the money they invested. Resolution: Judgment Rendered Sanctions: Injunction
Criminal- Final Disposition This type of disclosure event involves a criminal charge against the broker that has resulted in a conviction, acquittal, dismissal, or plea. The criminal matter may pertain to any felony or certain misdemeanor offenses, including bribery, perjury, forgery, counterfeiting, extortion, fraud, and wrongful taking of property.	<u>Charges</u> Count #1 attempt stealing $500.00 by deceit Amended Charges: Making a false report Amended Charge Type: Misdemeanor Amended Charge Disposition 2 yrs. probation & $500.00 fine
Customer Dispute- Award/Judgment	<u>Allegations</u> Clients allege that recommendation of Freddie Mac and Fannie Mae preferred shares were unsuitable for their account and represented as "safe".

This type of disclosure involves a final, consumer-initiated, investment-related arbitration or civil suit containing allegations of sales practice violations against the broker that resulted in an arbitration award or civil judgment for the customer.	Damage Amount Requested $25,000.00 Damages Granted $25,000.00
Customer Dispute- Settled This type of disclosure event involves a consumer-initiated, investment-related complaint, arbitration proceeding or civil suit containing allegations of sale practice violations against the broker that resulted in a monetary settlement to the customer.	Allegations Customers alleged the representative's recommendation to invest in a limited partnership, in February 2009, was not appropriate. Customers have alleged damages as noted below. Damage Amount Requested $175,000.00 Settlement Amount $145,000.00
Employment Separation after Allegations This type of disclosure event involves a situation where the broker voluntarily resigned, was discharged, or was permitted to resign after being accused of (1) violating investment-related statutes, regulations, rules or industry standards of conduct; (2) fraud or the wrongful taking of property; or (3) failure to supervise in connection with investment-related statutes, regulations, rules or industry standards of conduct.	Adviser's affiliation was terminated for his failure to disclose a regulatory inquiry and subsequent consent order by the Ohio Department of Insurance to the firm.
Regulatory- Final This type of disclosure event may involve (1) a final, formal proceeding initiated by a regulatory authority (e.g., a state securities agency, self-regulatory organization, federal regulatory such as the Securities and Exchange Commission, foreign financial regulatory body) for a violation of investment-related rules or regulations; or (2) a revocation or suspension of a broker's authority to act as an attorney, accountant, or federal contractor.	At the time of an on-site examination of the adviser in 2008 by the Office of Compliance Inspections and Examinations ("OCIE"), the adviser had violated securities laws by failing to complete an annual compliance review in 2006, making misleading statements on the adviser's website regarding the adviser's exclusive access to an investment firm's funds, omitting disclosures in its performance information that were required by the adviser's own policies and procedures, and making misleading statements in its performance information by providing model results that did not deduct the adviser's advisory fees. Following the examination, OCIE staff sent the adviser a letter concerning these violations. Despite assurances that it would take corrective action to remedy these violations, the adviser continued to violate

	securities laws at the time of OCIE's 2011 examination by failing to complete an annual compliance review in 2009 and by continuing to make misleading statements regarding its access to an investment firm's funds in its marketing materials. The adviser also misleadingly represented in one location on its website that it had over $600 million in assets when it reported in its Form ADV that it had less than $325 million in assets under management as of September 2011.

Appendix C: Multinomial Logit Regression

This appendix describes our Table 4, Panel B multinomial matching regression that explicitly models how all realized auditor-BD matches compare to other feasible matches. We use a multinomial logit to estimate the matching process between auditors and BDs. Each BD is matched to the audit office that provides the best match of all potential auditors. This setup allows us to test whether certain variables affect the probability of matching while considering other feasible matches.

We define feasible matches based on the BD's ownership and business model. We assume that publicly held (carrying; retail) BDs can only be matched with auditors with at least one publicly held (carrying; retail) BD. We assume that privately held, non-carrying, and non-retail BDs can be matched with any auditor client subject to the other constraints (e.g., a non-carrying BD that is publicly held can match to any auditor, so long as the auditor has at least one publicly held client—regardless of carrying status). We define the latent value of the match between BD *i* and auditor *j* at time *t* as

$$V_{i,j,t} = \alpha_{i,t} + \beta x_{i,j,t} + \varepsilon_{i,j,t} \ ,$$

where the vector *x* contains characteristics of the match, β is a vector of coefficients, and the stochastic terms ε are independently distributed as type-1 extreme value. Because we compare actual and feasible matches for the same BD at a point in time (the intercept $\alpha_{i,t}$ varies by BD-year), our specification accounts for time factors and BD unobservables that could otherwise confound our analysis. The probability that BD *i* and auditor *j* are matched (denoted as $P_{i,j,t}$) is equal to the probability that

$$V_{i,j,t} > V_{i,k,t} \text{ for all feasible matches } k \in K_{i,t},$$

where $K_{i,t}$ denotes the set of feasible matches for BD *i* at time *t*. We find estimates of the parameters β by maximizing the log likelihood function

$$\log L = \sum_{i=1}^{N} \sum_{k \in K_{i,t}} D_{i,k,t} \log P_{i,k,t},$$

where $D_{i,k,t}$ takes a value of one if BD *i* and auditor *k* matched at time *t*, and zero otherwise. It follows from the distributional assumption on our error term that probability $P_{i,j,t}$ equals

$$P_{i,j,t} \equiv \frac{\exp[V_{i,j,t}]}{\sum_{k \in K_{i,t}} \exp[V_{i,k,t}]} = \frac{\exp[\beta(x_{i,j,t} - x_{i,1,t})]}{\sum_{k \in K_{i,t}} \exp[\beta(x_{i,k,t} - x_{i,1,t})]}$$

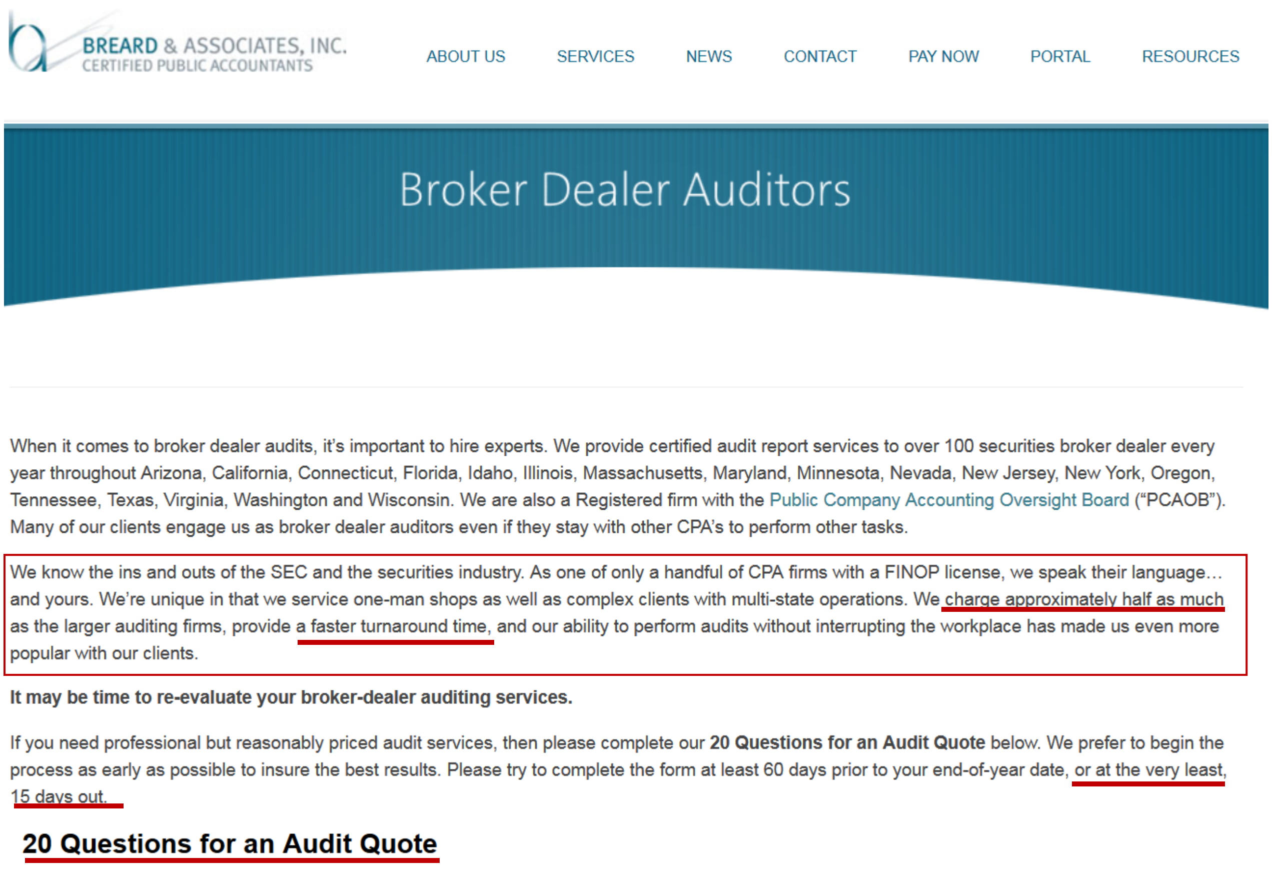
The term on the right of the last equality, which differences the regressors from the values for the arbitrary first option in BD i's choice set $x_{i,1,t}$, is used for econometric identification of β. The BD-year specific intercept $\alpha_{i,t}$ is not identified.

For characteristics of the match, we include the difference in both size and misconduct between the BD and the auditor's other clients, and the distance between the BD and the auditor's office. All characteristics are lagged by one year.

The difference in misconduct is measured as the absolute value of the difference between the BD's record of misconduct (*Misconduct Ever*) and average value of this variable for the auditor's other clients. The difference in size is measured as the absolute value of the difference between the BD's *Log Adviser Count* and average *Log Adviser Count* of the auditor's other clients. Distance is measured as the square root of the miles between the BD and the auditor (measured using spherical trigonometry). The square root is taken to reduce the right skew. As in Table 3, we estimate this regression using only new matches. Using differences in this specification, rather than including the BD and auditor characteristics separately, enables us to directly test whether these differences affect the probability of matching.

Figure 1: Auditor Reputation, Client Screening, and Audit Pricing

Below is a screenshot from Breard & Associates' website in 2018, before the audit firm was barred by the PCAOB. Note that the website changed after the barring, so we sourced the screenshot using Wayback Machine, an internet archive. Prior to 2018, Breard was one of the auditors with a large market share in high misconduct BD clients.



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20 Questions for an Audit Quote

Figure 2: Example Financial Adviser Record on FINRA

Table 1: Sample Selection

This table describes the construction of our sample using Audit Analytics and FINRA's BrokerCheck database.

Total observations in Audit Analytics (2001-2017)	83,823
Less:	
Incomplete filings	(2,551)
Duplicates	(3,561)
BD-Years	77,711
Less:	
Unable to match to FINRA BrokerCheck data	(1,763)
Non-U.S. or missing location	(1,168)
Missing leverage	(372)
Final Sample: BD-Years	74,408
New relationship sample not missing controls or lagged values (Tables 3-5): BD-Years	6,894

Table 2: Summary Statistics

This table summarizes the BD, audit, and misconduct variables for observations in our sample. See Appendix A for variables definitions.

Panel A: BD Variables

	Mean	Std Dev	25%	50%	75%	N
Total Assets ($000s)	1,002,174	15,100,000	121	556	3,780	74,408
Leverage	0.30	0.27	0.07	0.22	0.46	74,408
Adviser Count	155.45	1,132.09	4.00	10.00	32.00	74,408
Publicly Held BD	0.07	0.26	0.00	0.00	0.00	74,408
Carrying Type	0.20	0.40	0.00	0.00	0.00	74,408
Retail BD	0.48	0.50	0.00	0.00	1.00	74,408
BD Age	13.86	11.33	5.00	11.00	20.00	74,408
Average Adviser Experience	14.46	6.93	9.61	13.21	18.00	74,408
Average Adviser Qualifications	2.12	0.67	1.79	2.16	2.50	74,408
Asset Growth	0.35	1.51	-0.17	0.02	0.29	66,233
Adviser Growth	0.10	0.36	-0.02	0.00	0.16	66,233

Panel B: Audit Variables

	Mean	Std Dev	25%	50%	75%	N
Big N Auditor	0.19	0.39	0.00	0.00	0.00	74,408
IC Material Weakness	0.05	0.22	0.00	0.00	0.00	74,408
Going Concern	0.02	0.13	0.00	0.00	0.00	74,408
Audit Office Client Count	19.72	26.08	2.00	7.00	26.00	74,408

Panel C: Misconduct Variables

	Mean	Std Dev	25%	50%	75%	N
BD Misconduct Current	0.01	0.05	0.00	0.00	0.00	74,408
BD Misconduct Ever	0.12	0.19	0.00	0.05	0.17	74,408
BD Disclosure Current	0.02	0.06	0.00	0.00	0.00	74,408
BD Disclosure Ever	0.15	0.20	0.00	0.07	0.22	74,408

Table 3: Auditor-Client Matching by Size and Misconduct

This table provides non-parametric analysis of size and misconduct matches between BDs and auditors. In Panel A, we assign BDs to size terciles based on their *Adviser Count*, and auditors to size terciles based on the size terciles of their average client. In Panel B, we assign BDs to misconduct terciles within their size tercile based on their rate of *BD Misconduct Ever*. We assign auditors to misconduct terciles based on the misconduct tercile of their average client. We tabulate BD and auditor terciles from the year before their match, to avoid a spurious positive correlation between BD and auditor tercile assignments. Each cell in the 3 x 3 table reports the percent of BDs in their size or misconduct tercile that matched with a particular auditor size or misconduct tercile. For example, the first row of Panel A shows that for size tercile 1 BDs, 48.9% (34.1%; 17.0%) have an auditor in size tercile 1 (2; 3). The row below each table reports the expected probability of each type of match under the null hypothesis that there is no matching on size or misconduct. We report the Pearson's chi-squared test statistic for independence in auditor and BD characteristics at the bottom of the panel.

Panel A: Size Matching

		Auditor Size Tercile		
		1	2	3
BD	1	48.8%	34.5%	16.7%
Size	2	35.9%	35.9%	28.1%
Tercile	3	18.2%	27.1%	54.7%
	Null	34.5%	32.5%	33.0%

Test of independence for auditor and BD size:
Chi-square: 884.98
P-value: 0.000

Panel B: Misconduct Matching

		Auditor Misconduct Tercile		
		1	2	3
BD	1	35.2%	37.4%	27.4%
Misconduct	2	38.1%	37.5%	24.4%
Tercile	3	19.5%	38.5%	42.0%
	Null	30.7%	37.8%	31.5%

Test of independence for auditor and BD misconduct:
Chi-square: 257.38
P-value: 0.000

Table 4: Auditor-Client Matching by Size and Misconduct

This table models auditor-client matches as a function of BD size, misconduct, and other characteristics. Panel A employs OLS specification (1). The dependent variable in column 1 (2) is *Log Auditor Median Client Size* (*Log Auditor Misconduct Ever*), the natural logarithm of one plus the adviser count of the auditor's median client (*BD Misconduct Ever* averaged across clients). The dependent variable in column 3 is *Auditor Misconduct Tercile*, the misconduct tercile assigned in Table 3. Panel B employs a multinomial logit matching regression that compares realized matches to feasible matches, as described in Appendix C. The regression studies how differences in auditor and BD variables affect the probability of matching. In both panels, the sample is restricted to the first year of each audit office-BD relationship, and the unit of observation is BD-year. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

Panel A: Linear Regression

	(1) Log Auditor Median Client Size	(2) Log Auditor Misconduct Ever	(3) Auditor Misconduct Tercile
Log BD Adviser Count	0.198***	-0.006***	-0.016
	[12.20]	[-5.29]	[-1.15]
Log BD Misconduct Ever	-0.628***	0.071***	
	[-6.71]	[6.79]	
BD Misconduct Tercile			0.098***
			[8.01]
Leverage	-0.159***	0.003	0.122***
	[-3.07]	[0.70]	[3.18]
IC Weakness	-0.258***	0.018*	0.045
	[-4.39]	[1.94]	[0.83]
Going Concern	-0.106	-0.001	-0.032
	[-1.46]	[-0.15]	[-0.50]
Log BD Age	0.018	-0.002	-0.013
	[1.12]	[-1.49]	[-0.97]
Log Average Adviser Experience	-0.183***	0.018***	0.093***
	[-4.50]	[4.92]	[3.63]
Average Adviser Qualifications	0.017	0.002	0.014
	[0.81]	[1.30]	[0.88]
Publicly Held BD	0.868***	-0.023***	-0.188***
	[8.78]	[-6.73]	[-4.52]
Retail BD	0.063**	-0.012***	-0.069***
	[2.02]	[-4.29]	[-3.24]
Carrying Type	0.407***	-0.022***	
	[7.49]	[-7.68]	
Log Total Assets			-0.053***
			[-8.04]
Asset Growth			-0.037***
			[-7.37]
Adviser Growth			0.021
			[0.91]
Adj R-Sq.	0.289	0.157	0.193
N	6,894	6,894	6,894
Cluster by Audit Office	Yes	Yes	Yes
District x Year FEs	Yes	Yes	Yes
BD Size Tercile x Year FEs	No	No	Yes
Carrying Type x Year FEs	No	No	Yes

Panel B: Multinomial Logit Matching Regression

	(1)	(2)
Abs Difference in Misconduct	-1.392***	
	[-8.61]	
Abs Difference in Misconduct (BD higher)		-1.256***
		[-3.00]
Abs Difference in Misconduct (Auditor higher)		-1.456***
		[-4.51]
Abs Difference in Size	-0.337***	-0.338***
	[-14.12]	[-14.21]
Distance	-0.137***	-0.137***
	[-20.59]	[-20.57]
Bayesian information criterion	65,075	65,083
BD observations	6,216	6,216

Table 5: Auditor-Client Matching Robustness and Generalizability Analysis

This table provides robustness and generalizability analyses of our Table 4, Panel A column 3 results using specification (1). The dependent variable is *Auditor Misconduct Tercile*. Panel A employs alternative misconduct measures, whereas Panel B studies alternative samples of BDs based on their business type. In Panel A, column 1 we examine a narrower set of non-reporting misconduct. Column 2 examines this misconduct variable for BDs with inherently low audit risk: those that are publicly held, carry customer assets, have experienced an IC material weakness or going concern opinion, or participate in the MBS market. In Panel B, column 1 and 2 (3 and 4) limits the sample to relationships involving large and small BDs (publicly and privately held BDs), respectively. Column 5 (6) estimates specification (1) on public companies using the incidence of AAERs (meet-or-beat) as our reputation measure. The sample in all columns is restricted to the first year of each audit office-BD relationship. The unit of observation is BD-year. Our tests include the controls from specification (1), but we do not report them for brevity. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

Panel A: Robustness Analysis

	(1) Auditor Misconduct Tercile	(2) Auditor Misconduct Tercile
	Non-Reporting Misconduct	Low Audit Risk, Non-Reporting Misconduct
BD Misconduct Tercile	0.101***	0.110***
	[8.13]	[7.07]
Adj R-Sq.	0.159	0.103
N	6,894	4,063
Cluster by Audit Office	Yes	Yes
Controls	Yes	Yes
District x Year FEs	Yes	Yes
BD Size Tercile x Year FEs	Yes	Yes
Carrying Type x Year FEs	Yes	Yes

Panel B: Generalizability Analysis

	(1) Auditor Misconduct Tercile	(2) Auditor Misconduct Tercile	(3) Auditor Misconduct Tercile	(4) Auditor Misconduct Tercile	(5) Auditor Misconduct Tercile	(6) Auditor Misconduct Tercile
	Large BDs	Small BDs	Public BDs	Private BDs	Public Firms AAERs	Public Firms Meet or Beat
BD Misconduct Tercile	0.167***	0.062***	0.115*	0.097***		
	[6.70]	[3.53]	[1.80]	[7.61]		
Firm Misconduct Tercile					0.071**	0.036*
					[2.01]	[1.82]
Adj R-Sq.	0.211	0.119	0.204	0.174	0.139	0.172
N	2,284	2,370	500	6,394	6,080	1,733
Cluster by Audit Office	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
District x Year FEs	Yes	Yes	Yes	Yes	No	No
Census Region x Year FEs	No	No	No	No	Yes	Yes
BD Size Tercile x Year FEs	No	No	Yes	Yes	No	No
Firm Size Tercile x Year FEs	No	No	No	No	Yes	Yes
Carrying Type x Year FEs	Yes	Yes	Yes	Yes	No	No

Table 6: Auditor Reputation and Client Misconduct

This table models the misconduct tercile of the auditor's clients as a function of their portfolio exposure using the *Auditor Misconduct Tercile* assigned in Table 3 as the dependent variable. *Bank Exposure* is an indicator for auditors with bank clients. *No Public Exposure* is an indicator for auditors with no publicly held clients. *IPO Exposure* is an indicator for auditors with an IPO client last year, this year, or next year. The unit of observation is audit office-year. The sample in column 5 is restricted to audit firms with at least two offices. Our tests include the controls for the average client characteristics from specification (1), but we do not report them for brevity. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Auditor Misconduct Tercile	(2) Auditor Misconduct Tercile	(3) Auditor Misconduct Tercile	(4) Auditor Misconduct Tercile	(5) Auditor Misconduct Tercile
Bank Exposure	-0.263***			-0.198***	-0.064
	[-6.99]			[-5.17]	[-1.30]
No Public Exposure		0.156***	0.104***	0.084***	0.012
		[5.17]	[3.38]	[2.75]	[0.24]
IPO Exposure			-0.296***	-0.258***	-0.124***
			[-7.39]	[-6.42]	[-3.00]
Adj R-Sq.	0.166	0.164	0.17	0.173	0.302
N	20,512	20,512	20,512	20,512	7,189
Cluster by Audit Office	Yes	Yes	Yes	Yes	Yes
Controls (Average of Clients)	Yes	Yes	Yes	Yes	Yes
District x Year FEs	Yes	Yes	Yes	Yes	Yes
Audit Firm x Year FE	No	No	No	No	Yes

Table 7: Misconduct Mismatch and Relationship Length

This table models auditor-client relationship length as a function of the BD-auditor misconduct match. The dependent variable is *Relationship Length*, the number of years between the first and last appearance of the BD-auditor pair in the data. *Difference in Misconduct* is the absolute value of the difference between the BD's *Misconduct Ever* rate and the average rate for the auditor's clients. *Match* $1_A, 1_{BD}$ is an indicator for instances where an auditor and BD both belong to the '1' misconduct tercile defined in Table 3. Other 'Match' indicators follow the same convention. *Log # Auditors Near BD* is the log number of audit offices within 100 miles of the BD. The sample is limited to the latest year that each BD-auditor pair appears in the data. The unit of observation is BD-year. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Relationship Length	(2) Relationship Length	(3) Relationship Length	(4) Relationship Length
Abs Difference in Misconduct	-1.936***			
	[-5.99]			
Match 1_A, 1_{BD}		0.736***	0.686***	0.759***
		[6.08]	[5.82]	[5.51]
Match 2_A,2_{BD}		0.387***	0.324**	0.339**
		[2.90]	[2.48]	[2.26]
Match 3_A,3_{BD}		0.214	0.161	0.188
		[1.34]	[1.02]	[0.99]
Match 1_A,3_{BD}		-1.010***	-0.950***	-0.983***
		[-4.44]	[-4.21]	[-3.99]
Match 3_A,1_{BD}		-0.425*	-0.482**	-0.535*
		[-1.74]	[-1.98]	[-1.87]
Log # Auditors Near BD				-0.066
				[-1.37]
Adj R-Sq.	0.213	0.219	0.222	0.187
N	14,651	14,651	14,651	12,118
Cluster by Audit Office	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Size Match Indicators	No	No	Yes	No
District x Year FEs	Yes	Yes	Yes	No
BD Size Tercile x Year FEs	Yes	Yes	Yes	Yes
Carrying Type x Year FEs	Yes	Yes	Yes	Yes

Table 8: Misconduct Transparency and Audit Office Portfolio Concentration

This table models audit office portfolio concentration as a function of misconduct transparency. The dependent variable is *Std Deviation Client Misconduct*, the dispersion of *Misconduct Ever* across clients within an audit office-year. *Transparency* is an indicator variable equal to one for 2008 and 2009, and zero for 2005 and 2006. We limit the sample to these years. Column 3 omits auditor offices with BD clients participating in the Mortgage Backed Securities market. The unit of observation is audit office-year. Our tests include the controls for the average client characteristics from specification (1), but we do not report them for brevity. Reported below the coefficients are t-statistics calculated with standard errors are clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1) Std Dev Client Misconduct	(2) Std Dev Client Misconduct	(3) Std Dev Client Misconduct
	+/-2 years	+/-2 years	+/-2 years
Transparency	-0.015***	-0.015***	-0.015***
	[-3.49]	[-3.43]	[-2.72]
Adj R-Sq.	0.756	0.763	0.761
N	2,552	2,356	1,936
Cluster by Audit Office	Yes	Yes	Yes
Controls (Average of Clients)	Yes	Yes	Yes
Audit Office FEs	Yes	Yes	Yes
Client Product Offering FEs	No	Yes	Yes
Omit Offices with MBS Clients	No	No	Yes

Table 9: Auditor Type and Future Misconduct

This table models the BD's future misconduct as a function of the auditor they match with. Except for column 2, the dependent variable is the average rate of *BD Misconduct Current* over future years, as labeled. In column 2, the dependent variable is the average rate of *BD Non-Reporting Misconduct Current*. *High Misconduct Auditor* is an indicator equal to one (zero) for BDs with a tercile 3 (1 or 2) misconduct auditor. *BD Misconduct Current*$_{Year0}$, *BD Misconduct Ever*$_{Year0}$, and *Auditor Misconduct Ever*$_{Year0}$ are measured the year before the audit relationship formed. The sample in all columns is restricted to the first year of each audit office-BD relationship. Column 6 further restricts the sample to audit relationships with high misconduct BDs. The unit of observation is BD-year. Our tests include the controls from specification (1), but we do not report them for brevity. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample of BDs					High Mis. BDs
	BD Misconduct Current Year 1	BD Non-Reporting Misconduct Current Year 1	BD Misconduct Current Year 1	BD Misconduct Current Years 1-2	BD Misconduct Current Year 1	BD Misconduct Current Year 1
High Misconduct Auditor	0.005***	0.004**		0.006***	0.005***	0.009**
	[3.03]	[2.27]		[4.01]	[2.76]	[2.13]
BD Misconduct Current$_{Year0}$	0.248***	0.244***	0.247***	0.190***	0.227***	0.255***
	[2.91]	[2.87]	[2.90]	[2.73]	[2.61]	[2.72]
Auditor Misconduct Ever$_{Year0}$			0.029***			
			[3.85]			
BD Misconduct Ever$_{Year0}$					0.022***	
					[4.11]	
Adj R-Sq.	0.117	0.118	0.119	0.098	0.122	0.139
N	4,822	4,822	4,822	4,822	4,822	1,521
Cluster by Audit Office	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
District x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
BD Size Tercile x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Carrying Type x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes

Online Appendix to:

Auditors are Known by the Companies They Keep

August 2019

This online appendix tabulates additional analyses not reported in the paper.

Table A1: Auditor-Client Matching by Size and Misconduct- Alternative Approaches

This table repeats our Table 3 analysis using alternative measurement approaches and samples. In Panel A, we assign BDs to size terciles based on their *Total Assets*, and auditors to size terciles based on the size terciles of their average client. In Panel B, we assign BDs to misconduct terciles within their asset-based size tercile according to their rate of *BD Misconduct Ever*. We assign auditors to misconduct terciles based on the misconduct tercile of their average client. In Panel C (D) we study misconduct matching for auditors with (without) publicly held clients. In these two latter panels, auditors are assigned to misconduct terciles within their respective group (those with or without publicly held clients). We tabulate BD and auditor terciles from the year before their match, to avoid a spurious positive correlation between BD and auditor tercile assignments. Each cell reports the percent of BDs in their size or misconduct tercile that matched with a particular auditor size or misconduct tercile. The row below each table reports the expected probability of each type of match under null hypothesis that there is no matching on size or misconduct.

Panel A: Size Matching

		Auditor Size Tercile		
		1	2	3
BD Size Tercile	1	53.0%	33.5%	13.5%
	2	37.2%	38.2%	24.7%
	3	11.7%	26.4%	61.9%
	Null	34.2%	32.7%	33.1%

Panel B: Misconduct Matching

		Auditor Misconduct Tercile		
		1	2	3
BD Misconduct Tercile	1	33.8%	35.0%	31.2%
	2	34.7%	35.9%	29.4%
	3	23.2%	34.6%	42.1%
	Null	30.5%	35.1%	34.3%

Panel C: Misconduct Matching for Auditors with Publicly Held Clients

		Auditor Misconduct Tercile		
		1	2	3
BD	1	45.2%	28.1%	26.7%
Misconduct	2	41.3%	30.8%	27.8%
Tercile	3	27.6%	29.6%	42.7%
	Null	39.8%	29.2%	31.0%

Panel D: Misconduct Matching for Auditors without Publicly Held Clients

		Auditor Misconduct Tercile		
		1	2	3
BD	1	26.0%	38.0%	36.0%
Misconduct	2	28.2%	36.7%	35.1%
Tercile	3	19.3%	36.8%	43.9%
	Null	23.6%	37.3%	39.1%

Table A2: Auditor-Client Matching by Size and Misconduct- Structural Estimation

This table presents the results of our structural estimators. We refer the reader to Logan, Hoff, and Newton (2008) and Akkus, Cookson, and Hortacsu (2015) for details of these estimators.

In Panel A, we present results of a model based on matching under non-transferable utility as in Logan, Hoff, and Newton. We make three modifications to Logan, Hoff, and Newton's estimator. First, rather than estimating preferences for both parties, we treat BDs as having heuristic preferences—preferring the closest auditor. This modification lessens concerns that the parameters of the auditor's utility function are not identified. Second, we use a flat, improper prior on all coefficients instead of a Gaussian prior. Using a flat prior avoids inducing a potential bias toward the prior mean. Note that using a flat prior results in Gaussian marginal posterior distributions for the coefficients. Third, to adapt this procedure for many-to-one matching, we follow Chib and Greenberg (1998) and model obtainable non-matches as providing the auditor with lower utility than matches. This extension of Logan, Hoff, and Newton is straightforward. We estimate the marginal posterior distributions of the coefficients using 10,000 iterations of a Gibbs sampler, with the first 5,000 iterations serving as the burn-in. Gelman-Rubin statistics indicate convergence of the chains. We provide posterior means of the coefficients with the ratio of the posterior mean to the standard deviation in square brackets.

In Panel B, we present estimates based Akkus, Cookson, and Hortacsu's estimator for matching under transferable utility. As in Akkus, Cookson, and Hortacsu, we randomly sample matches for each year. To adapt this estimator for many-to-one matching, we first randomly sample 50 auditors that gained a new BD client, then randomly sample one of the auditor's new matches. Since our sampling procedure results in unequal probabilities of selection, consistency does not directly follow from the results cited by Akkus, Cookson, and Hortacsu. In square brackets, we present 95% confidence intervals using the same subsampling procedure as Akkus, Cookson, and Hortacsu. We use 100 subsamples of approximately 30% of the sample. *, **, *** indicate that zero is not contained in the 90%, 95%, and 99% confidence intervals, respectively.

Panel A: Estimator based on Logan, Hoff, and Newton (2008)

	(1)	(2)
Abs Difference in Misconduct	-0.148	
	[-3.499]	
Abs Difference in Misconduct (BD higher)		-0.105
		[-2.784]
Abs Difference in Misconduct (Auditor higher)		-0.978
		[-9.711]
Abs Difference in Size	-0.112	-0.108
	[-19.361]	[-17.785]
Distance	-0.054	-0.054
	[-121.451]	[-113.828]

Panel B: Estimator based on Akkus, Cookson, and Hortacsu (2015)

	(1)	(2)
Abs Difference in Misconduct	-712.500**	
	[-899.952, -86.115]	
Abs Difference in Misconduct (BD higher)		-483.853*
		[-815.025, 102.356]
Abs Difference in Misconduct (Auditor higher)		-780.746**
		[-921.799, -66.825]
Abs Difference in Size	-118.403***	-122.920**
	[-675.251, -71.297]	[-690.453, -55.440]
Distance	-76.691***	-70.187***
	[-514.732, -49.673]	[-440.567, -48.594]

Table A3: Auditor-Client Matching Robustness Analysis

This table provides robustness analyses of our Table 4, Panel A column 3 results. The dependent variable in columns 1 and 2 is *Auditor Misconduct Tercile*, the misconduct tercile assigned in Table 3. The dependent variable in column 3 (4) is *Auditor Regulator Misconduct Tercile* (*Auditor Disclosure Tercile*), the auditor's tercile with respect to regulator-reported misconduct (all disclosures as opposed to just misconduct disclosures). The dependent variable in column 5 is *Auditor Misconduct Current Rate*, the *BD Misconduct Current* rate averaged across clients. Column 1 limits the sample to BDs whose prior auditor exited the BD market. Column 2 adds product group x year fixed effects to equation (1). The misconduct variables in column 3 (4; 5) consider only regulator-reported incidents (all incidents reported to BrokerCheck regardless of their severity; the *BD Misconduct Current* rate). The sample is restricted to the first year of each audit office-BD relationship. The unit of observation is BD-year. Reported below the coefficients are t-statistics calculated with standard errors clustered at the audit office level. *, **, *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively. See Appendix A for variables definitions.

	(1)	(2)	(3)	(4)	(5)
	Auditor Misconduct Tercile	Auditor Misconduct Tercile	Auditor Regulator Misconduct Tercile	Auditor Disclosure Tercile	Auditor Misconduct Current Rate
	Forced Exits	Product x Year FE	Regulator Ever	Disclosure Ever	Misconduct Current Rate
BD Misconduct Tercile	0.124***	0.078***			
	[3.39]	[5.22]			
BD Regulator Misconduct Tercile			0.091***		
			[6.75]		
BD Disclosure Tercile				0.118***	
				[9.63]	
BD Misconduct Current					0.023*
					[1.91]
Adj R-Sq.	0.238	0.199	0.095	0.200	0.016
N	513	4,967	6,894	6,894	6,894
Cluster by Audit Office	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
District x Year FEs	Yes	Yes	Yes	Yes	Yes
BD Size Tercile x Year FEs	Yes	Yes	Yes	Yes	Yes
Carrying Type x Year FEs	Yes	Yes	Yes	Yes	Yes
BD Product Offering x Year FEs	No	Yes	No	No	No